Exploring opportunities for the integration of GNSS with forest harvester data to improve forest management

A thesis submitted in partial fulfilment of the
requirements for the
Degree of Doctor of Philosophy
in Forest Engineering

by

Ernesto Alejandro Olivera Farias

University of Canterbury

2016

Table of contents

Abstract

Worldwide approximately 3 billion m^3 of wood is harvested and removed from forests annually. Forest plantations play an important role in forest harvesting providing 46% of the total industrial roundwood produced in the world, while they account for only 7% of the world's forested area. Modern harvesting systems are mechanised for productivity, costs, and safety reasons. Due to the advances and availability of both computing and sensor technologies, mechanised machinery is a platform for integration of these technologies with electronic control systems capable of monitoring machine functions, estimating measurements, and recording data.

One of the most popular mechanized harvesting systems is Cut-To-Length (CTL). The CTL system typically consists of two types of machines, a harvester, which fells and processes the trees into logs in the stand, and a forwarder that extracts the logs. CTL machines were developed in Scandinavia and are now used worldwide. They are the preferred technology for harvesting fast growing forest plantations in some South American countries such as Uruguay.

Harvesters are equipped with a system called StanForD that provides a mechanism to automatically record data from forest harvesters in a series of file formats. When harvesters are equipped with a Global Navigation Satellite System (GNSS) receiver, these data include a locational reference and a time stamp.

GNSS-enabled data provide site-specific information that is a valuable input for both stand level forest management and harvesting operation assessment. The objective of this thesis is to demonstrate the usefulness of GNSS-enabled StanForD files as a tool for evaluating variables affecting harvesting operations and the forest management process. To achieve the objective two independent studies were carried out.

Chapter 2 explores opportunities to manage harvesting operations. The goal of this study was to demonstrate the effectiveness of using the geospatial and time information contained in StanForD files to model harvester productivity. A harvester dataset obtained from Uruguay comprised over 63,000 cycles of felled and processed stems (stm files) and 1440 shift hours (drf files). With two thirds of this cycle time data, a mixed effects model was fitted to evaluate harvester productivity as a function of stem diameter at breast height (DBH), species, shift (day/night), slope, and operator. A slope surface derived from a digital terrain model was overlaid with GNSS stem records. The reserved third of the data was used to validate the model. DBH was the most influential variable in harvester productivity, showing a positive correlation and a R^2 value of 0.73 in the validation model. Operator and species also had significant effects. There was

no significant slope effect, whereby the study area only had flat and mildly sloping terrain. Shift did not have a significant effect, indicating there was no drop in night shift productivity. The model developed constitutes the first published harvester productivity model in South America based on data automatically collected by harvesters.

Chapter 3 and 4 explore opportunities to provide feedback to improve the forest management process using the site-specific harvester data. Stand productivity of fast-growing forest plantation varies across short distances depending on site and forest characteristics. As plantation forest silviculture is typically resource intensive in establishment, forest management would benefit from a site-specific approach. A tool to characterize such stand productivity variations are yield maps and a cost effective source of data is automatically collected by harvesters. To create such maps we need to understand the effect of geospatial accuracy of tree location recorded by the harvester.

The objective of Chapter 3 is to improve our understanding of spatial resolution for studying variations in volume and stocking across forested stands, and establish guidance for actual spatial resolution that would allow the development of fit-for-purpose forest yield maps from harvester data. This study investigated data sets from seven stands: two had very accurate tree location, and five were harvester data files that have inaccuracy associated with both the GNSS recording under forest canopy and the physical dislocation of the GNSS relative to the harvested tree location. The GNSS unit is on the cabin of the machine, but the tree is felled using a boom and could be up to 12 meters from the cabin. A spatial resolution for studying variations in stand productivity and stocking across stands was established to allow the development of forest yield maps from harvester data. By assessing the variability across a range of cell sizes, it was concluded that a cell size between 40 and 60 m is suitable to use as a reference for calculating volume per hectare and stocking.

Based on the outputs of Chapter 3, the objective of Chapter 4 was to develop models to map stand productivity from GNSS enabled harvester data. This chapter first explores several models using the same two stands with accurate tree location used in Chapter 3. It assesses their accuracy, then applies the models to the harvester data stands, and finally compares the results of the models to determine the most suitable models. The assessment of the models includes the comparison of productivity maps created from inventory plots.

Chapter 5 is a synthesis of the findings, contributions, limitations of the studies, and views on future research needs resulting from this work.

Key words: StanForD files, GNSS, *Eucalyptus* spp., Uruguay, harvester, productivity model, forest productivity maps, Geostatistics.

Acknowledgments

I want to acknowledge the financial support received from the School of Forestry – University of Canterbury through the T. W. Adams Scholarship. Future Forest Research Ltd., Rotorua, New Zealand funded the study expenses.

I would like to express my gratitude to my senior supervisor Associate Professor Rien Visser. He inspired me to choose this project topic, supported my application to the scholarship and guided me to consistently carry on with the project and overcome the challenges I found. I would also like to thank my assistant supervisors Dr Justin Morgenroth and Dr Mauricio Acuna. Both have provided helpful comments, suggestions and constructive criticism to improve the quality of my work. I really appreciate the help with the statistical analysis from Associate Professor Luis Apiolaza, along with his enthusiasm and suggestions for the project.

Thanks to the Uruguayan forest company Montes del Plata (MdP). I left the company after 6 years of working with them, a year later, I knocked on their doors a site to collect data and they selflessly allowed me to collect data from the company's operations. They also provided the complementary inventory data. The management team made this decision together, so thanks to Moacyr Fantini, Diego Carrau, Juan Bide, Martim Terra, Nicolas Perdomo and specially my former boss, Francisco Ferreira. I value the time and effort Martin Arocena, Diego Cooper and Alejandra Reinoso dedicated to send the data and answer my questions.

Ponsse Uruguay S.A. made possible the data collection in Uruguay as they showed interest in the idea of the project. They downloaded and sent the data from MdP operations and also provided a copy of the harvester control system software that helped with the data processing; so thank you Martin Toledo and Daniel Alfaro.

I would also like to thank Timothy Mc Donald and Christian Brodbeck from Auburn University, USA. They kindly shared data presented as Stand 1 in Chapters 2 and 3.

Several people and companies in New Zealand contributed to the initial stages of the project. I am grateful to Adam Brand and Adrian from Brand Logging; Brett Key, Gerard Crichton from Waratah NZ; Mark Dean from Ernslaw One Ltd; Darren Mann and Erin Poulson from Rayonier Matariki Forests, Tony from EMS Rotorua and John Arlinger from Skogforsk, Sweden.

To my partner and best friend Cecilia, you have been my inspiration, support and the best companion I could ask to undertake this journey. Along with her, I want to dedicate this work to my daughter Rafaela, who arrived last year; she has made this journey much more exiting and pleasant and has been that extra motivation to complete the PhD.

Publications and complementary work

Journal Articles

The contents of Chapter 2, 3 and 4 of this thesis have been published, submitted, and prepared for publication respectively as:

Olivera, A., Visser, R., Acuna, M., & Morgenroth, J. (2015). *Automatic GNSS enabled harvester data collection as a tool to evaluate factors affecting harvester productivity in a Eucalyptus spp. harvesting operation in Uruguay*. International Journal of Forest Engineering. doi: 10.1080/14942119.2015.1099775

Olivera, A., & Visser, R. (2016). *Development of forest-yield maps generated from global navigation satellite system (GNSS) enabled harvester StanForD files: preliminary concepts.* New Zealand Journal of Forestry Science. DOI: 10.1186/s40490-016-0059-x

Olivera, A., Visser, R., & Morgenroth, J. Forest yield map from GNSS enabled harvester data: developing maps (in prep)

Published reports, technical notes and conference contributions

Olivera, A., & Visser, R. (2016). Using the harvester on-board computer capability to move towards precision forestry. NZ Journal of Forestry. 60(4).

Olivera, A., & Visser, R. (2015). Data capture from harvester on-board computers. Harvesting technical note HTN08-03. Future Forest Research Ltd. Rotorua, New Zealand.

Olivera, A., & Visser, R. (2014) Integration of Harvester Data and Geospatial Information. Harvesting technical note HTN07-03. Future Forest Research Ltd. Rotorua, New Zealand.

Olivera, A., & Visser, R. (2014, March). The integration of GPS in harvesters as a tool for site specific management in plantation forests. Paper presented at the 6th Precision Forestry Symposium: The anchor of your value chain, Stellenbosch, South Africa.

Olivera, A., Visser, R., Morgenroth, J., & Acuna, M. (2014). Integration of GNSS in harvesters as a tool for site-specific management in plantation forests; a literature review. F. F. R. Ltd. (Ed.), Technical reports (pp. 14). Future Forest Research Ltd. Rotorua, New Zealand.

Selected presentations and University of Canterbury engagement

- 2012-2014 Teaching Assistant, course Foundation of Engineering (ENGR101); Lab tutorials.
- 2012 July, Presentation of the research proposal, Postgraduate seminar. Department post graduate seminar series.
- 2014 May, Precision Forestry applied to Forest Operations, Guest lecturer, course Geospatial Technologies in Forestry (FORE342).
- 2014 July, Future Forest Research members meeting, Rotorua, Project update.
- 2015 June, Exploring opportunities of the integration of GNSS in harvesters, Guest speaker, industry workshop: Managing Data and Wood flow from Mechanised Harvesters, Rotoura, New Zealand.

List of tables

List of figures

Chapter 1: Introduction

Worldwide approximately 3 billion m^3 of wood is harvested and removed from the forest annually as raw material for the production of goods (industrial roundwood) or for energy generation (Köhl et al., 2015). Forest plantations play an important role in forest harvesting providing 46% (0.77 billion of m^3) of the total industrial roundwood produced in the world, while it accounts for only 7% or the total forested area (Payn et al., 2015).

Modern harvesting systems are mechanised for productivity, costs, and safety reasons. The favourable conditions of forest plantations with defined rows and even aged stands contribute to more efficient harvesting operations. Due to the advances and availability of both computing and sensor technologies, mechanised machinery is a platform for integration of these technologies with electronic control systems able to monitor machine functions, estimate measurements and record data.

One of the most popular mechanized harvesting systems is Cut-To-Length (CTL). The CTL system is typically consists of two types of machines, a harvester, which fells and processes the trees into logs in the stand, and a forwarder that extracts the logs. CTL machines were developed in Scandinavia and now are used worldwide and they are the preferred technology for harvesting fast growing forest plantations in some South American countries.

For example, production forests in Uruguay increased rapidly from less than 100,000 hectares in 1990 to approximately 990,000 in 2012. *Eucalyptus* species, mostly planted for the pulp and paper industry, account for 73% of this area while pine plantations represent 26% (MGAP, 2014). Accompanying this increase in the planted area, the harvesting activity has been growing steadily over the last decade from 5.1 to 12.4 million m^3 harvested annually from 2004 to 2014 (MGAP, 2015). Cut-To-Length (CTL) machines are the preferred technology for harvesting in Uruguay; estimates indicate that over 60% of the wood harvested each year come from a CTL system. Moreover, these machines have been widely adopted by other countries in the region such as Brazil and Chile.

Harvesters are equipped with a standard for data collection and communication called StanForD that provides a mechanism to automatically record data from forest harvesters. There are more than 20 standard files produced when operating with StanForD, including: apt (cross-cutting instructions), prd (production files), pri (production individual files), drf (operational monitoring data) and stm (individual stem data) (Skogforsk, as cited in Olivera and Visser (2014)). The apt files are produced by the user, whereas the other files are generated by the machine's computer. The StanForD standard has been refined over time and the new version StanForD2010 is already available in some new machines; nevertheless, the information contained in the files is similar.

Stm files compress detailed production data of each harvested tree and corresponding cut logs, including: all diameter sections measured at 10 cm intervals, diameter at breast height (DBH), individual log volume, stem volume, log classification, stem identification number, and commercial height. When harvesters are equipped with a Global Navigation Satellite System (GNSS) receiver, these data include a locational reference and (in some machines) a time stamp. This data, plus the detailed information on the use of time during the operation recorded in drf files, form the basis of the data and information used in this thesis.

Several opportunities to utilise this harvester based comprehensive data collection system have been explored for forest management and research applications. Examples include, production reports, harvesting productivity evaluations and the validation of estimates of tree location and stem attributes derived from airborne laser scanning (ALS). There is potential to further explore the advantages of the addition of GNSS to the system, in order to make both the harvesting operation and the forest management process more efficient. This is particularly true in South America where use of the technology has been mostly oriented to production reporting from the operation.

Most harvester productivity studies in South America to date have been carried out using traditional manual methods. A great advantage of the use of StanForD files is the low cost and efficiency of collecting a large amount of data. The data used in this thesis is from a single harvester that provided more than 63000 useful cycles (trees felled) and over 1400 hours of records. It was downloaded by a Uruguayan based company employee and processed by the author in New Zealand. In comparison, a manual time study completed by Olivera and Perdomo (2011) required five researchers to be in the forest for 10 days each to record 127 hours of felling of a total of 6118 cycles (trees felled).

From the forest management point of view, GNSS-enabled stm and pri files provide site-specific information that is a valuable input for stand level management. Reliable stand productivity information at the time of harvest would make it possible to evaluate and manage the development of future stands by knowing the site variability and adjusting the silvicultural practices accordingly. This would be an alternative to managing stands based on average characteristics provided by inventory plots, which is the prevalent approach for forest plantations management.

Variability in productivity across forested areas has been study based on inventory plots; although, forest inventories are designed to give estimate of the total volume for the stand. More recently in the mid-1980s the use of Light Detection and Ranging (LiDAR) has been introduced and can be used at active company forest sites (Rombouts et al., 2010). Both are costly methods and the level of detail depends heavily on the sample intensity. With access to a georeferenced census of all harvested trees (e.g. harvester data) the site variability can be determined on a smaller scale, without additional costs of data collection. How specifically forest plantations can be managed, is an arguable topic, especially in large scale plantation forests. This opportunity to quantify the variability within stand using an established and integrated data collection system will certainly bring benefits to intensively managed forest plantations. In plantation forests in countries such as Brazil and Uruguay, the length of the rotations has been reduced to 6-8 and 9-12 years, respectively, due to intensive breeding programs and improvement in silvicultural operations. Moreover, both countries have started to adopt technology for site-specific management of silviculture operations (in the establishment phase), frequently based on technologies and equipment used in agriculture and later adapted to forestry machines. They include the use of GPS guidance and quality control in soil tillage and GPS controlled equipment for the application of agrochemicals. The application of these technologies also includes the management of the information generated, for example application maps, initial assortment and plants localization, quality control, and machine performance assessment (Vieira et al., 2012).

OBJECTIVES AND OVERVIEW

The objective of the thesis is to demonstrate the usefulness of GNSS enabled StanForD files as a tool for evaluating variables affecting harvesting operations and the forest management process. The diagram in Figure 1 presents the opportunities identified and developed in this thesis. To achieve the objective, two independent studies, each with separate specific objectives, were carried out to prove the usefulness of the technology. The studies are presented in three manuscript style chapters that include the relevant literature review. The first study is presented in Chapter 2, whereas the second study, as it is more complex, is divided in two chapters (Chapter 3 and 4).

The goal of the study presented in Chapter 2 is to demonstrate the effectiveness of using GNSS enabled StanForD files (stm and drf files) to model harvester productivity using the geospatial and time information contained in the files; and present a model to predict harvester productivity for Uruguayan conditions. It explores the advantages of the integration of both technologies from the harvesting management point of view. Harvesting a timber resource represents a relatively high proportion of the delivered wood cost. As such, the productivity of harvesting systems is a widely studied topic worldwide, including the use of harvester data. Models to predict harvester productivity still need to be developed based on local data because there are many stand and terrain factors affecting productivity that vary depending on regional conditions (Hiesl and Benjamin, 2013). The development of a productivity model based entirely on harvester data collection using GNSS-enabled stm and drf files is a case study without precedents in fast growing South American forest plantations. The model presented includes five variables that affect harvester productivity, including slope obtained from separate GIS files through an overlay analysis.

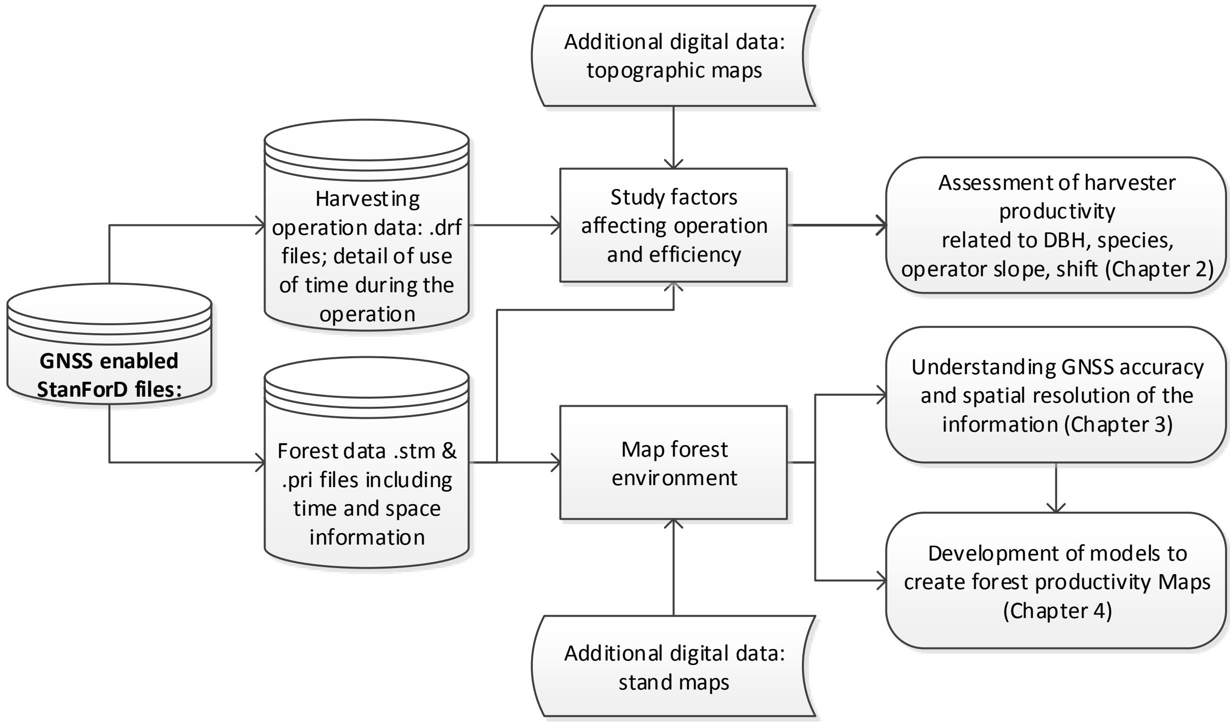

Figure 1: General scheme of the opportunities identified and explored from the use of StanForD files.

The objective of Chapter 3 is to improve our understanding of spatial resolution for studying variations in volume and stocking across forested stands. It establishes guidance for the spatial resolution that would allow the development of fit-for-purpose forest yield maps from harvester data. This is a required step before the development of forest yield maps presented in Chapter 4. It supports the creation of productivity maps based on the real harvested volume as per the machine measures and records, and first studies the spatial resolution we can achieve dealing with GNSS accuracy issues, namely GNSS location and accuracy under forest cover. The study then explores the variability of productivity in forested areas using two model stands with accurate tree location and compares it with five harvester data stands.

The objective of Chapter 4 is to develop models to map productivity from GNSS enabled harvester data. The resolution used for the models is that established in Chapter 3. Several models were explored using the two stands with accurate tree location. Their accuracy was assessed and then applied to the harvester data stands. The results of these models were evaluated and compared to decide which is most accurate and suitable. The assessment of the models includes the comparison productivity maps created from inventory plots.

The thesis ends with a synthesis (Chapter 5) of the findings, contributions, limitations of the studies, and views of the future research needs based on this work.

DATA SOURCES

Harvester data/StanForD files

The main dataset for the study comprises stm and drf files retrieved from a single-grip harvester Ponsse Ergo 8W equipped with a specialised harvester head designed for processing and debarking eucalypts (Ponsse H7euca), and a combined GSM-GNSS antenna fitted on the cabin for geospatial data collection and communication. The control system is Opti4G 4.715, which complies with the StanForD standard. This machine was one of a team of five harvesters and three forwarders working in CTL harvesting operations in *Eucalyptus* spp. plantations in Uruguay. All harvested stems were debarked for pulpwood at a standard log length of 6.5 m, and a second grade variable length logs between 4 m and 6.5 m. All diameter measurements and volume estimations expressed of this data are under bark, unless otherwise specified.

The harvested areas are located in the northern part of the Rio Negro department in Uruguay (32°33’18”S, 57°24’19”W) (Figure 2), and belong to the company Montes del Plata. The areas include four species of *Eucalyptus*, and were harvested between March and October 2014. The climate in the region is classified as Cfa according to Köppen–Geiger climate classification system, with an annual average temperature of 17.5°C, around 1200 mm of annual rainfall evenly distributed during the year (Instituto Uruguayo de Meteorología, n.d.). The relief is with gentle slopes, mostly below 6%, occasionally over 12%. Soils in the area are loam, predominantly deep and with medium level of fertility (MGAP, 2008b).

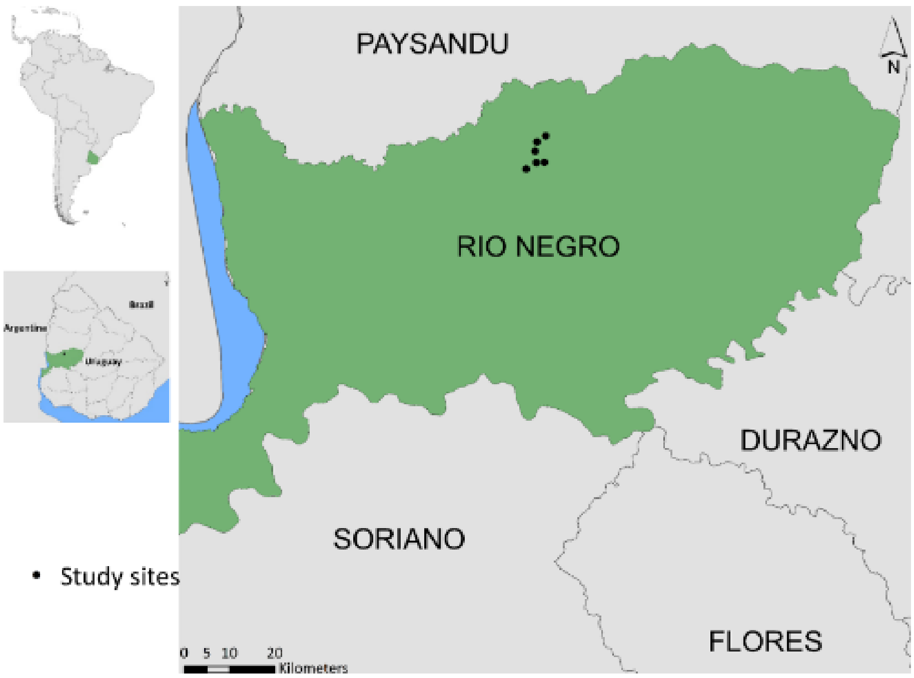

Figure 2: Geographic location of the study sites.

While StanForD files contain useful data, the process of extracting, storing and analysing the data is complex. The data contained in the files is available as unformatted text file (.txt). The data is arranged using two codes, called 'variable' and 'type', to standardise data capture for specific parameters, followed by the actual data that is being recorded. Each set of variable, type and datum is separated from the next set by a tilde (~) (Skogforsk, 2007). Part of a StanForD data record for an individual tree along with an explanation of the data is shown in Table 1.

Table 1: Part of a stm file for a single harvested stem and explanation of the data. The first row shows the form the data is displayed in the original text file. The body of the table explains the meaning of the information contained.

110 2 1~**270** 1 27~**270** 2 0~**270** 3 27~**38** 1 J Cabrera~**38** 4 0~**38** 5 0~**523** 1 3257956~**523** 2 2~**523** 3 5740183~**523** 4 2~**523** 5 101~**523** 6 20140522212527~

Register	Explanation	Information contained
110 2 1~	Variable 110 type 2	Species code, e.g. 1 = *Eucalyputs*
270 1 27~	Variable 270 type 1	Stem identity = 27^{th} tree harvested for the harvesting unit
270 2 0~	Variable 270 type 2	0 means no information contained
38 1 J Cabrera~	Variable 38 type 1	Machine operator = J Cabrera
523 1 3257956~	Variable 523 type 1	GNSS Latitude = 32.57956^o
523 2 2~	Variable 523 type 2	Latitude 2 = Southern hemisphere
523 3 5740183~	Variable 523 type 3	GNSS Longitude = 57.40183^o
523 4 2~	Variable 523 type 4	Longitude 2 = Western hemisphere
523 5 101~	Variable 523 type 5	GNSS altitude = 101 m above sea level
523 6 20140522212527~	Variable 523 type 6	Felling date and time: year 2014, month 05, day 22, hour 21, minutes 25, seconds 27

Figure 3 shows the process followed to format the data from stm files in tabular order on a spreadsheet. A total of 67,581 stem/tree records from stm files and 1,448 work hours from drf files were the size of the harvester data used in all studies. In Chapter 2, 63,717 and 1,414 shift hours were used. In Chapters 3 and 4 only the data from stands that were harvested completely (Figure 4) were selected: 5 stands totalling 29,180 stem records and 32.4 hectares.

Additional data

The Montes del Plata company also provided inventory data in digital format from pre-harvest inventory (PHI) carried out in 2013. This data comprised georeferenced plots with individual tree data for the majority of the area, stand maps, historical information (year of plantation), species and genetic material.

The data presented as Stand 1 in Chapters 3 and 4 was a surveyed stand located 9.6 km north of Auburn Alabama (32°41'43" N, 85°30'11" W) in the United States. Each tree's position within the stand was measured with sub-centimetre accuracy as described in Brodbeck et al. (2007). The information contained in this dataset was tree identity; X, Y and Z coordinates; and DBH.

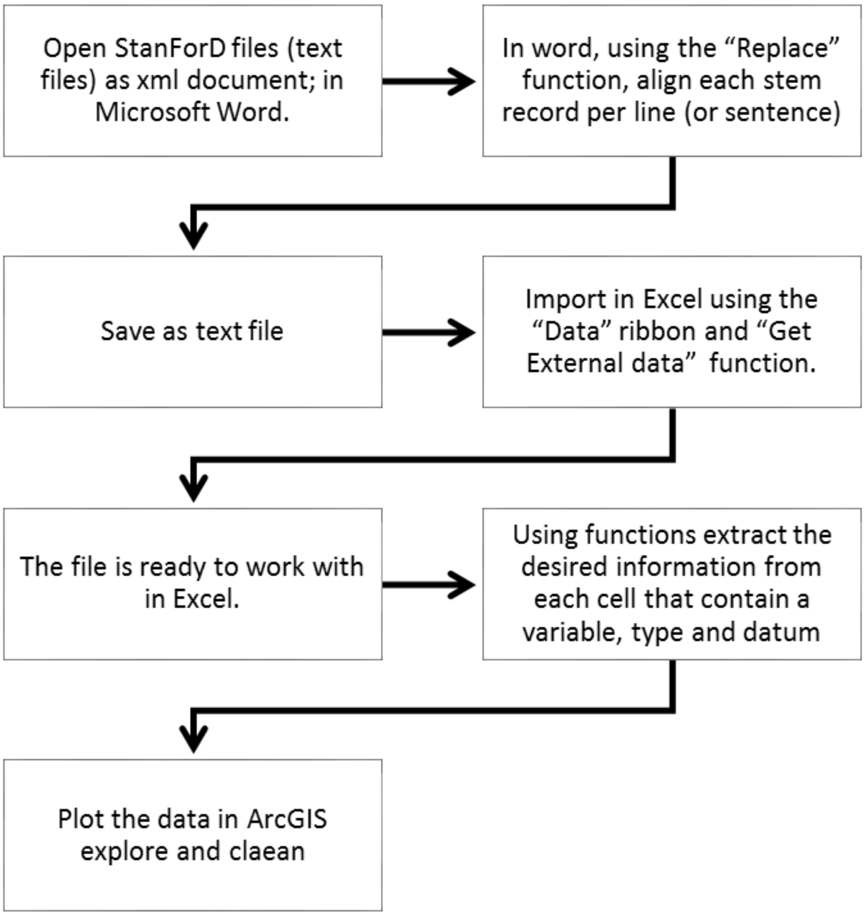

Figure 3: Process used for extracting data from stm StanForD files

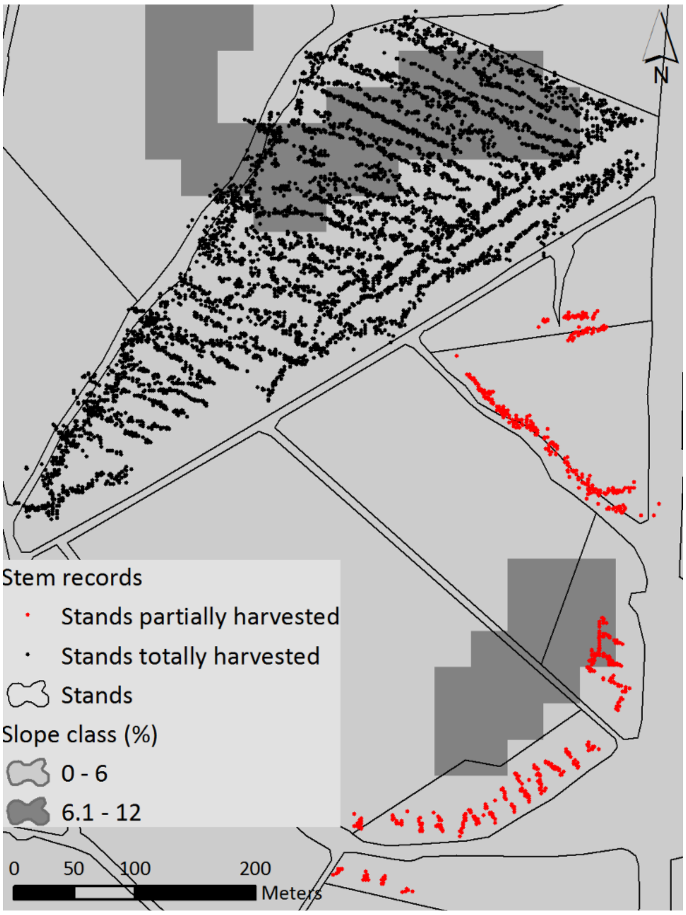

Figure 4: Part of the study areas showing stand boundaries, slope classes and a typical pattern of stem records from harvester data. In black, stem records of a stand the machine harvested completely and in red, stem records of stands harvested partially

Chapter 2: Automatic GNSS-enabled harvester data collection as a tool to evaluate factors affecting harvester productivity in a *Eucalyptus* spp. harvesting operation in Uruguay

The contents of this chapter have been published as:

Olivera, A., Visser, R., Acuna, M., & Morgenroth, J. (2015). *Automatic GNSS enabled harvester data collection as a tool to evaluate factors affecting harvester productivity in a Eucalyptus spp. harvesting operation in Uruguay*. International Journal of Forest Engineering. doi: 10.1080/14942119.2015.1099775

ABSTRACT

Uruguay has adopted cut-to-length (CTL) machines in forest harvesting operations, especially in large scale, fast-growing plantations. The majority of modern CTL machines have on-board computers that capture individual tree data and can be coupled with global navigation satellite systems (GNSS). This provides the opportunity to collect data for research purposes and to improve operations. In this study, data (StanForD stm and drf files) were retrieved from a GNSS-enabled harvester working in CTL operations in *Eucalyptus* spp. plantations in Uruguay. With two thirds of this data a mixed effects model was fitted to evaluate harvester productivity as a function of stem diameter at breast height (DBH), species, shift (day/night), slope, and operator. A slope surface derived from a digital terrain model was overlaid with GNSS stem records. Slope values were assigned to each stem using the Spatial Analyst toolbox in ArcGIS. The reserved third of the data were used to validate the model. DBH was the most influential variable in harvester productivity, showing a positive correlation and a R^2 value of 0.73 in the validation model. Operator and species also had significant effects. There was no significant slope effect, whereby the study area only had flat and mildly sloping terrain. Shift did not have a significant effect, indicating there was no drop in night shift productivity. The model developed constitutes the first published harvester productivity model in South America based on data automatically collected by harvesters. In addition, the forestry company may benefit from using the model for operator management.

Keywords: StanForD files, GNSS, *Eucalyptus* spp., Uruguay, harvester, productivity model

INTRODUCTION

The forestry sector in Uruguay has grown considerably in the last few decades. Production forests increased quickly from less than 100,000 hectares in 1990 to 990,030 in 2012. Cut-to-length (CTL) machines developed in Scandinavia have been widely adopted in harvesting operations in South American countries such as Uruguay, Brazil and Chile. The CTL system is typically made up of two types of machines, a harvester, which fells and processes the trees into logs, and a forwarder that extracts the logs. In Uruguay, although there is no official data available, it is estimated that over 60% of the 10 million cubic meters harvested each year (MGAP, 2014) is harvested using CTL systems.

Harvesters are equipped with a system for data collection and communication called StanForD that provides a mechanism to automatically record data from forest harvesters.

There are a number of standard files produced when operating with StanForD, including: apt (cross-cutting instructions), prd (production files), pri (production individual files), drf (operational monitoring data) and stm (individual stem data) (Skogforsk, as cited in Olivera & Visser 2014). apt files are produced by the user, whereas the others are produced by the machine computer. These files can be used by forestry companies and contractors to manage production aspects and have been used in numerous research applications. For example, stm files were used to validate estimates of tree location and stem attributes derived from airborne laser scanning for a forest area without manual measurements (Holmgren et al., 2012). This technique has proven useful as a tool for pre-harvest inventory (Barth and Holmgren, 2013). (Murphy et al., 2006) analysed the implications of using the harvester measurement optimizer as an alternative for pre-harvest inventory sampling by using the harvester measurement system to evaluate the predictions of harvest inventory. Purfürst and Erler (2011a) used various StanForD file types (prd, pri, drf and stm) to quantify operator influence on harvesting productivity, analysing data from 3351 stands, 32 operators and three harvester types over a period of three years in thinning operations in East and South Germany. In another study using the same data, Purfürst (2010) assessed the learning curve of harvester operators. Purfürst and Lindroos (2011b) compared the performance of 12 operators contrasting two methods, short-term subjective ratings and long-term output data based on StanForD files. Passicot and Murphy (2013) studied the effect of length of shift in operators' productivity in Chile using production and down time data recorded by the machines' on board computers (OBC).

Several studies have explored and validated automatically recorded data for machine productivity modelling in large-scale forest management scenarios (i.e. several machines, years, stands, species and operators). Gerasimov et al. (2012) used StanForD production files and TimberLink 2.0 software for a study in Russia using records from 38 harvesters over a two year period. Heinimann (2001) in central Europe developed a model using over 2200 records from 12 different types of harvesters at a harvest unit level. Furthermore, Eriksson and Lindroos (2014) modelled harvester and forwarder productivity in Sweden from comprehensive company records and established a harvester productivity model that included more than 20 variables.

A more detailed approach for modelling harvesting productivity is to use individual tree data, recorded as stm and hvp files from StanForD and StanForD2010 versions respectively. Strandgard et al. (2013) proved that time stamp on stm files are a valid option for harvester productivity estimation. They calculated cycle time by subtracting time stamps from consecutively processed trees in CTL operations in Australia. Similarly, Arlinger and Möller (2014) used the software TimberLink (Deere & Company) and hvp files to carry out a time study. In both studies, results were compared against traditional manual methods for validation and results did not differ significantly. However, basing a productivity study only on time stamps from StanForD data does have limitations if not coupled with direct observation or video recording. For example, separate elements of the cycle time cannot be identified; it is difficult to identify delays within the cycle time; and the data cannot be analysed relative to stand and terrain factors such as tree form, branch size, multiple leaders, ground roughness, or the effect of weather conditions such as rain due to the lack of direct observation.

The majority of modern CTL machines' OBC have the option to integrate a global navigation satellite system (GNSS) receiver. Arlinger and Möller (2007) showed that when equipped with a GNSS receiver, the OBC can also record geographic coordinates for each harvested stem in the forest. As such, with the GNSS function enabled, stm files record not only the time stamp for each felled stem but also geographic coordinates. This creates opportunities to study the effect of site variables on harvesting productivity over a larger scale and at a lower cost than using traditional methods.

Some issues have limited the use of StanForD files to develop productivity models. The need to standardize terminology for automatic time study based on individual stem records has been analysed by Palander et al. (2013) who noted restrictions due to potential confusion or incapacity of the system to reliably identify all components within the cycle time. Moreover, the complexity of files and differences between control systems (manufacturers) makes the processing and filtering of data a challenging task (Purfürst as cited in Eriksson et al. (2014). Data ownership and its availability for public research is a sensitive topic, since the harvesting operation (and data collection) is carried out by contractors and the use of the data for public research is not always in the interests of those who own the data (CRC for Forestry, 2010). The quality of data can also limit its use for research purposes; a thorough use of the OBC with trained operators and managers, quality control, and frequent calibrations is paramount to ensure reliability of data (CRC for Forestry, 2010; Olivera et al., 2014).

Harvester performance in eucalypt plantations in South America has been studied using traditional manual methods and historical production records. Many studies have found significant differences in harvester's productivity, and hence, cost, related to manually measured slope (Fernandes et al., 2013;

Leite et al., 2014; Robert et al., 2013; Simões and Fenner, 2010). Leite et al. (2014) and Martins et al. (2009) studied the impact of planting spacing and stocking and established that higher stocking decreased harvester productivity due to the decreasing in tree size with increasing stocking. More comprehensive models considering individual tree volume, slope and direction of machine advance (uphill or downhill) were proposed by Leite et al. (2013). Based on historical records from the forest companies, Bramucci and Seixas (2002) modelled harvester productivity focusing their analysis on variables from the forest: average individual volume, mean DBH, mean height, and volume of wood per hectare in two scenarios, with or without debarking. The dataset comprised over 4 million m^3, 68 harvesters and 200,000 working hours. (Leonello et al., 2012) studied the effect of experience on harvester operator performance in eucalypt plantations.

Although GNSS-enabled stm files are now a readily available technology, only limited research has been published where both components were used. Cordero et al. (2006) assessed machine productivity and utilization in two different harvesting systems, namely CTL compared to a tree-length system comprising of a feller buncher and grapple skidder, by tracking machines with GNSS and using a Geographic Information System (GIS) that combined the machine's progress shape files with inventory layers based on plot samples. A recent approach using a digital terrain model (DTM) derived from light detection and ranging (LiDAR), proves the potential of developing harvester productivity studies using layers of digital information (Strandgard et al., 2014).

While models for estimating harvester productivity have been created worldwide, models still need to be developed based on local data because there are many factors affecting productivity that vary depending on conditions in the region (Hiesl et al., 2013).

The overall goal of this study was to demonstrate the effectiveness of using GNSS enabled StanForD files to establish harvester productivity. It included an evaluation of factors such as slope derived from a digital terrain model, and operator.

MATERIALS AND METHODS

Site location and data collection

The data for the study were retrieved from a single-grip harvester working in CTL harvesting operations in *Eucalyptus* spp. plantations. Each harvested unit corresponded to an even-aged, single species, first rotation stands. The operation ran from Monday to Friday in double shifts: the day shift from 7:00 to 17:30 and the night shift from 20:30 to 7:00; and Saturday from 7:00 to 15:00. All harvested production was debarked for pulpwood at a standard log length of 6.5m, and a second grade variable length logs between 3m and 6.5m. All diameter measurements and volume estimations expressed in this work are under bark, unless otherwise specified.

The harvested stands were located in the northern part of the Rio Negro department in Uruguay (Figure 2). These forest plantations belong to the company Montes del Plata.

The stands included four different species of *Eucalyptus*, two of which had two different age classes, and were harvested between March and October 2014 (Table 2). During this period, three different operators operated the harvester. Operators 1 and 2 had operated harvesters for more than 12 months which meets the criterion of being experienced as defined by Purfürst et al. (2011a). Operator 3 had 10 months of experience. All operators were trained by Ponsse professional instructors: 60 hours of theoretical training, 60 hours of practical training in simulators and 48 hours of practical training in the field. The training program included instructions to identify and record delay times as they happened during an operation. OBC measurement calibrations are performed weekly or when a new site is started (whichever happens first), or if a difference higher than 8% between inventory predictions and harvester records is detected, or when a sensor in the harvester head is fixed or replaced.

Table 2: Description of the forests and dataset. There are two stands of different ages for E. dunnii and E. maidenii

			E. bicostata [a]	*E. dunnii* [b]		*E. grandis* [c]	*E. maidenii* [d]	
Plantation characteristics [e]		Plantation age (years)	19	16	19	16	15	19
		Average DBHOB [f] (mm)	207	206	223	204	183	200
		Average volume ($m^3\ ha^{-1}$)	273	287	546	288	240	261
		Average height (m)	21.3	21.9	29.2	22.8	20.4	21.8
		Stocking (trees ha^{-1})	952	759	1000	682	933	781
		Mean tree volume (m^3)	0.29	0.35	0.55	0.39	0.26	0.35
Number of records	Day shift	Slope 0 - 6%	6028	2737	4080	4554	3762	10896
		Slope 6.1 - 12%	204	62	195	24	--	1274
	Night shift	Slope 0 - 6%	5555	2726	4048	3536	2942	9333
		Slope 6.1 - 12%	858	202	191	30	--	480

Note: [a] *Eucalyptus bicostata*, Maiden, Blakely & Simmons; [b] *Eucalyptus dunnii*, Maiden; [c] *Eucalyptus grandis*, W.Hill; [d] *Eucalyptus maidenii*, F.Muell; [e] Data from Pre-harvest inventory; [f] DBHOB = Diameter at breast height over bark

To model harvester productivity both individual tree registers and work statistics recorded under StanForD standard as stm and drf files respectively were used. A macro-enabled spreadsheet in Microsoft Excel 2013 was created to extract and manipulate the data from original text files.

Stem (.stm) files

Stem files (.stm) contain compressed data for each individual processed stem (tree), including but not restricted to: all diameter sections measured at 10 cm intervals, DBH, individual log volume, stem volume, log classification and stem identification number. The control system generates one stm file per day per site. Geographic coordinates of each tree were included in the files. From stm files, for each recorded stem were extracted: stem ID, geographic coordinates (latitude, longitude and altitude), DBH, harvested volume (total harvested volume), commercial volume (only commercial logs), commercial height, stem small end diameter (SED), time stamp (year, month, day, hour, minute and second) for when the tree was felled and operator identification. A shift (day/night) attribute was assigned to each stem according to the time stamp. Stm files also contain input information such as species and site (harvesting unit). This information was confirmed with the company's inventory data.

Geographic coordinates were used to create a shapefile of all stem records, which was overlaid on a slope surface to evaluate its effect on machine productivity (Figure 4).

With the time stamp records, cycle time was calculated for each individual tree by determining the difference between two consecutive stem's time stamps; this approach was used by Strandgard et al. (2013) and Arlinger et al. (2014). Cycle time therefore, is the time between two consecutive activations of the bar saw to fell a tree; it includes felling, moving the stem, debarking, delimbing, cross cutting and other times (e.g. brushing, moving residues and head positioning). The subtraction of consecutive tree records for cycle time calculation has the limitation that it is impossible to know from stm files only whether there was a delay hidden between two records. drf files were used to identify the cycles that include a delay.

Drf files

Drf are specific files for operational machine monitoring and contain detailed information on the use of time and mechanical events during the operation. The files can be site (object) or time oriented (Arlinger et al., 2011). Drf files contain records of the beginning and end of each subdivision of time during the operation (defined as sub-shift). The minimum duration of a down time is user-defined; for this operation it was 3 minutes. To reduce the influence of down and other times (terrain travel, other work, and road travel) in the cycle time; only the processing time (P0) component of the effective work time was used. P0 is defined by Arlinger et al. (2011), p.7: "harvesting head and linkage active" also called Main Work Time (MW) (IUFRO 1995). This concept excludes all down times and work times other than processing. Short delays below 15 seconds might be included as they are assigned to the previous sub activity by the system. Figure 5 illustrates the subdivision of time according to StanForD.

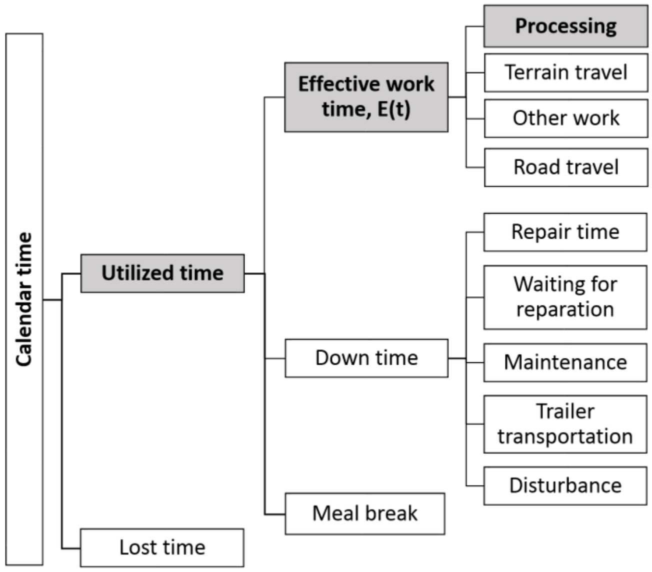

Figure 5: StanForD work divisions, highlighting the time division used in this work. Adapted from Arlinger et al. (2011) p 5.

From drf files, the beginning of each period of down time and work time was identified. With this information, stm files time stamps were cross-checked and excluded all records that had a delay or a work time other than processing. This was done to ensure that processing times were not overestimated.

Additionally, work statistics for the operation were calculated from drf files for each operator by species and age. Table 3 shows that the proportion of processing time ranged between 68% and 77% for all species and operators.

Slope

The slope surface was derived from digital terrain model (DTM) data obtained from the Uruguayan national database (Dell'Acqua, 2004; MGAP, 2008a) with a spatial resolution of 30 x 30 metres and a precision of interpolation between points of 2.5 metres. To determine the slope for each individual tree record, both layers of data were overlaid in ArcGIS (Esri Inc., 2014a) and each tree was assigned a corresponding slope based on XY coordinates (Figure 4). The slope values were then reclassified as a categorical variable into two classes, 0-6% and 6.1-12%.

Table 3: Proportion of time divisions as classified in Figure 5; includes total time. There are two stands of different ages for *E. dunnii* and *E. maidenii*

			E. bicostata	*E. dunnii*		*E. grandis*	*E. maidenii*	
		Age (years)	19	16	19	16	15	19
Machine times	Overall	Total assessed time (hrs)	286	99	238	188	164	439
		Effective work time (%)	75	84	79	81	77	80
		Processing time (%)	68	77	71	73	72	74
		Down time (%)	18	9	15	13	15	13
		Meal break (%)	7	7	7	6	8	7
		Processing/E (t) ratio (%)	92	92	90	91	93	93
	Operator 1	Total assessed time(hrs)	158	50	112	98	83	225
		Effective work time (%)	80	83	76	82	78	80
		Processing time (%)	74	76	68	74	73	74
	Operator 2	Total assessed time(hrs)	128	49	48	90	81	112
		Effective work time (%)	68	85	80	80	77	75
		Processing time (%)	62	79	74	73	72	70
	Operator 3	Total assessed time(hrs)	--	--	78	--	--	102
		Effective work time (%)	--	--	82	--	--	83
		Processing time (%)	--	--	73	--	--	78

Note: Processing time, Effective Work time, Down time and Meal break percentages are all relative to Utilized time.

Criteria for discarding data

From the original data set of 67581 trees harvested, 63717 were used. All trees that met at least one of the following criteria were discarded:

- A delay was included in the calculated cycle time; detected from analysis of drf files.
- 40mm > DBH > 400mm; 40mm is the minimum diameter in the company's specification, and the distribution of diameter estimations over 400mm was erratic suggesting edge trees or errors in automated measurement.
- Commercial height < 3.0m because this is the shortest pulp log length by the company's specifications.
- Top diameter >DBH; for consistency of stem shape and measurement.
- Cycle time < 0.20 minutes and > 6.2 minutes. These lower and upper limits on cycle time are based on previous research carried out in similar situations; i.e. same *Eucalyptus* species,

pulpwood debarked timber, 6.5m logs, same region of the country and similar ages (Cusano et al., 2009; Olivera et al., 2011).

Statistical analysis

The modelled (dependent) productivity variable is the quotient of stem commercial volume (calculated by the OBC) divided by the cycle time. The model considered the following independent variables: diameter at breast height (DBH), species, operator, shift, slope, and the interactions between DBH and species, and DBH and slope (see Appendix). Productivity was modelled using two thirds of the data set with the remaining third reserved to validate the model. A linear mixed effect model was developed to model the harvester productivity using the statistics software R (R Core Team, 2013) and nlme package (Pinheiro et al., 2014) using the maximum likelihood (ML) method. ML allows comparison between models using analysis of variance (ANOVA) (Crawley, 2013a) Mixed effects modelling is not a common approach to modelling forest machine productivity. However, it is a better option than linear modelling, since the model allows the use of fixed and random effects in the same model. In this case, it would not be appropriate to include the operator effect as a fixed effect, because operators have a more dynamic influence than machine and the environment (Lindroos, 2010). A disadvantage of mixed effects models is they do not generate an R^2 value, which is a numerical indicator of the proportion of the variability of the response variable explained by the model's explanatory variables. Nevertheless, the goodness of fit for a mixed effects model is expected to be at least as good as a linear model (Crawley, 2013a). Fixed effects variables were those from the environment, namely DBH, species, shift, and slope; whereas the human variable, operator, was considered to have a random effect. This approach allows a general model for harvester productivity to be created while evaluating and obtaining equations for each one of the operators involved in the study. To homogenise the variance of the dependent variable to improve fit, both productivity and DBH were transformed to their natural logarithms (Figure 6 and Figure 7).

A stepwise procedure was followed to obtain the final model, starting from a maximal model including all variables and the interaction between DBH and species, and DBH and slope (model 1 in Table 4) (Appendix). Then, variables with no statistically significant effect were excluded one by one from the model. ANOVA using Akaike's information criterion (AIC) at a 0.01 level of significance was used to compare models. The lower the AIC value, the better the fit of the model (Crawley, 2013b). The final model was checked for homoscedasticity and normality of errors.

To validate the model, a set of predicted productivity values was created using the model and compared with the reserved third of the data. Then a linear regression was fitted to assess the suitability of the model.

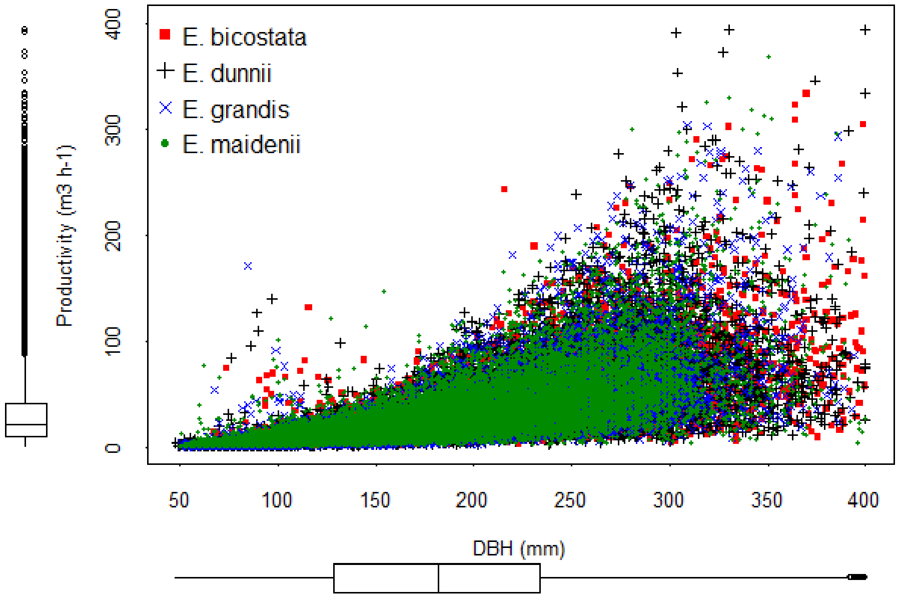

Figure 6: Graph of productivity per processing hour (all records) as a function of DBH and box plots showing distribution of points.

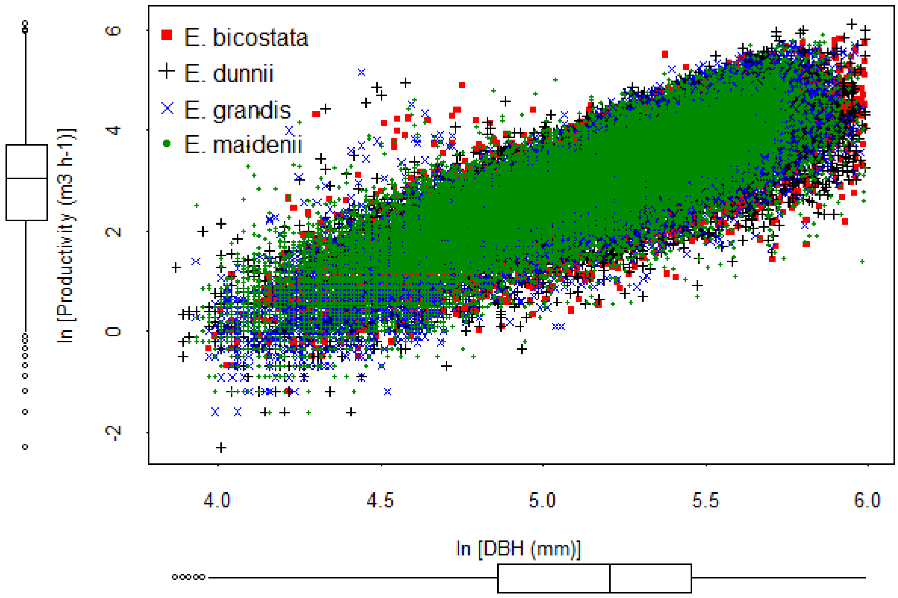

Figure 7: Graph of ln (productivity) as a function of ln (DBH) showing linear trend after transformation.

RESULTS

Model 4 was selected as the best model because it has the lowest AIC value and it includes the fewest explanatory variables, thus it is the simplest model (Table 4). It did not differ significantly from previous instances of the model (as evidenced by non-significant P values). Slope and shift did not significantly affect the productivity, and thus, were not included in the final model.

Table 4: Comparison of models in the stepwise procedure. All variables are included in model 1; variables with no significant effect were excluded in subsequent models one by one

Model	Variables			AIC	Comparison	P value
	Fixed effect	Interaction	Random effect			
1	DBH, Species, Shift, Slope	DBH x Species, DBH x Slope	Operator	73354.72	--	--
2	DBH, Species, Slope, Shift	DBH x Species	Operator	73355.22	1 vs 2	0.114
3	DBH, Species, Shift	DBH x Species	Operator	73353.98	2 vs 3	0.385
4	DBH, Species	DBH x Species	Operator	73353.31	3 vs 4	0.249

Equation (1) represents the productivity model and equation (2) is the resulting productivity equation. The species effect was significant and it is also of interest to quantify the species-dependent operator effect. There is a unique pair of values of the coefficients b0 and b1 for each combination of species and operator (Table 5). Figure 8 shows predicted productivity for both processing time (P0) and utilized time (Ut) for each species. While, Figure 9 presents predicted productivity for each combination of operator and species. The models were confirmed to be homoscedastic and errors were normally distributed.

$$\mathit{ln(Productivity)} = \mathrm{b0} + \mathrm{b1} * \mathit{ln(DBH)} \quad (1)$$

$$\mathit{Productivity} = e^{\mathrm{b0} + \mathrm{b1} * \mathit{ln(DBH)}} \quad (2)$$

The proportion of effective work time and processing time varied between 75% and 84 %, and 68% and 77% respectively depending on species. *E. bicostata* was at the low end and for 16 year old *E. dunnii* the proportions were the highest. These proportions also varied depending on operator (Table 3). Figure 8 shows the plotted equation for each species for processing time and utilized time as classified in Figure 5. The values for Ut were obtained multiplying the predicted productivity at P0 by an efficiency factor (Processing time/Utilized time) for the corresponding species. This approach can be applied for each operator, since there is both an equation to predict the productivity per processing hour and an efficiency factor for each operator.

Table 5: Model coefficients for species and operator.

Species	Model	Model coefficients b0	b1
E. bicostata	General	-8.68	2.24
	Operator 1	-8.55	2.24
	Operator 2	-8.82	2.24
E. dunnii	General	-9.36	2.38
	Operator 1	-9.23	2.38
	Operator 2	-9.50	2.38
	Operator 3	-9.34	2.38
E. grandis	General	-10.02	2.49
	Operator 1	-9.90	2.49
	Operator 2	-10.16	2.49
E. maidenii	General	-9.06	2.33
	Operator 1	-8.93	2.33
	Operator 2	-9.20	2.33
	Operator 3	-9.04	2.33

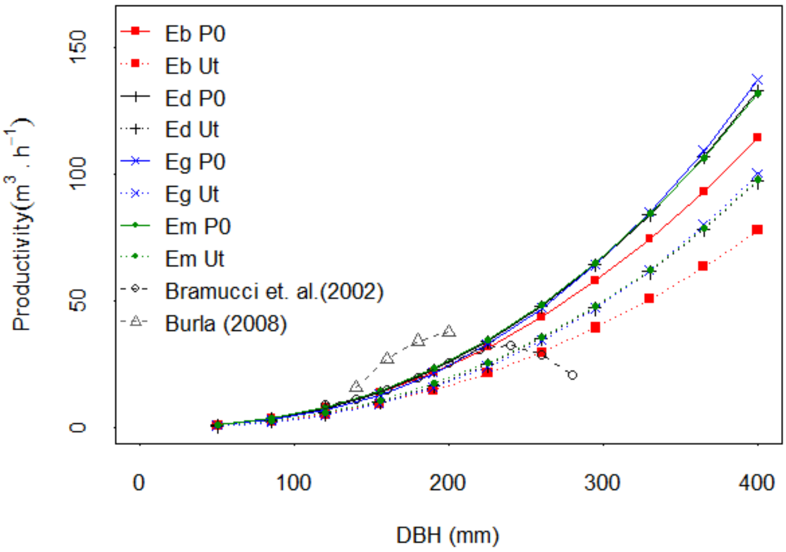

Figure 8: Productivity predictions by the model. Results expressed by species per processing time (P0) and utilized time (Ut) compared with two other published models Bramucci et. al. (2002) and Burla (2008). Eb: *Eucalyptus bicostata*, Ed: *Eucalyptus dunnii*, Eg: *Eucalyptus grandis*, Em *Eucalyptus maidenii*.

The R^2 of the validation model using the reserve dataset was 0.73, which indicates the model's predictions explain 73% of the variability in productivity using an independent dataset and the very low p value (< 0.001) indicates the significance of this result. Both the intercept and the slope of the validation model are within the expected values, approximately 0 and 1 respectively, as shown in Table 6. The validation model was checked for homoscedasticity and normality of errors.

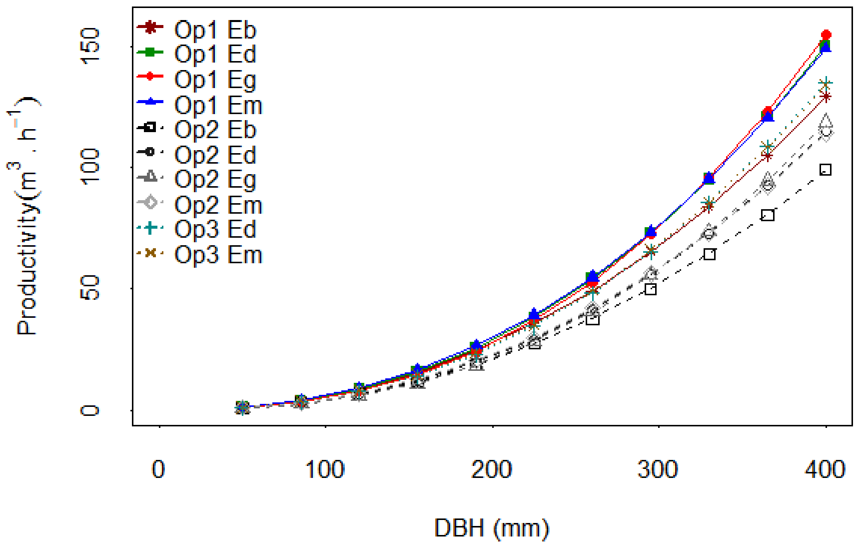

Figure 9: Productivity predictions by the model per operator by species per processing time (P0). Op1, Op2 and Op3: operator 1, 2 and 3 respectively

Table 6: Model validation information

		Confidence Interval		RMSE	P value	R^2
Coefficients	Value	0.5%	99.5%	--	--	--
Intercept	-0.017	-0.050	0.016	--	--	--
Slope	1.005	0.994	1.015	0.576	<0.001	0.73

DISCUSSION

DBH effect

As expected, productivity was correlated with DBH. The shape of the curve suggests an exponential response. Bramucci et al. (2002) at stand and shift level and Burla (2008) at plot level found a linear then decreasing trend (polynomial function) for *Eucalyptus* sp. debarked wood (Figure 8). Adebayo et al. (2007) reported linearly increasing productivity as DBH increased between 13 and 58 cm, which is comparable to Acuna and Kellogg (2009) who found the same result for DBH ranging from 13 to 41 cm.

Visser and Spinelli (2012) studied productivity as a function of individual tree volume and found that productivity increased at a decreasing rate until a point where the trees were too big and the machine struggled to process them. After this point, the productivity began to become more erratic and then eventually decreased. In our study, the productivity relative to DBH increased at an increasing rate. Productivity values for DBH values over 300 mm showed high levels of variability, which suggested a similar effect of a harvester starting to struggle to fell and process the trees efficiently. For the data set that was limited to 400 mm as the maximum DBH, this effect did not affect the trend (Figure 6 and Figure 8).

Figure 8 compares our model with the models developed by Bramucci et al. (2002) and Burla (2008). The values predicted for our model below 220 mm of DBH were similar to those resulting from the former, whereas values over 220mm were noticeably different given the different shape of the curve. Bramucci et al. (2002) however did not specify if the productivity was expressed for PMH (productive machine hours, equivalent to effective work time) or utilized time. The model from Burla (2008) on the other hand predicted higher values for the range between 140 and 200 mm. These results were for delay free PMH.

Species effect

Although the four species are all *Eucalyptus*, the species effect was significant in the study and had a significant interaction with DBH. Nevertheless, *E. dunnii* and *E. maidenii* had very similar productivity curves throughout the modelled DBH range. *E. grandis* showed lower productivity than *E. dunnii* and *E. maidenii* at values of DBH below 300 mm, whereas for larger trees, they were more productive to harvest but the differences were small. I would expect higher productivity for *E. grandis* and *E. dunnii* because these species are easier to debark and have a straighter shape. In addition, the effect of these species may be caused by the fact that the 16-year-old plantations had considerable lower stocking (Table 2) which suggested the forests had been thinned at some stage. *E. bicostata* was the least productive to harvest for DBH values over 200mm, this difference being more noticeable for larger trees. The differences in productivity for species were clearer when separated by operator as shown in Figure 9. The shape, health of trees, higher percentage of bark, and size of branches can be factors that explain the lower productivity for *E. bicostata*. Moreover, fungi frequently affect *E. bicostata* plantations in Uruguay, which makes the debarking process harder for harvesters, because the bark sticks to the stem in the affected trees and parts of the stem. These factors can also affect the efficiency of the operation, as there was a lower proportion of effective work time (higher down times) for this species. None of these variables were captured by harvesters' OBC, which is a limitation of this approach.

The differences in harvester productivity between *E. dunnii*, *E. grandis* and *E. maidenii* were relatively small. For a more generic productivity model, it would be possible to use only one general model. However, this approach has shown that differences can and do exist, and individual equations can be developed especially if anticipating that larger differences can be observed if using volume as a piece size variable.

Operator effect

Although they each undertook a similar training program, the three operators included in the study had consistent differences in harvesting performance for all species. These differences matched the "ranking" of operators' performance based on interviews with the company regarding their operators (Manager pers. comm.). Operator 1 was the most productive and operator 2 the least productive, though both had 12 months of experience. Despite having only 10 months of experience, operator 3 had average productivity, which indicated that experience does not necessarily explain performance. For example, for *E. maidenii* at DBH of 200mm operator 1 outperformed operators 2 and 3 by 30% and 11%, respectively (Figure 9). These results were consistent with other studies that encountered large differences between operators working in similar conditions. Purfürst et al. (2011a) reported that at the stand level, operators differed by a factor of 2.2 working in thinning operations in Germany. Likewise, Kariniemi, and Ryynänen and Rönkkö (as cited in Ovaskainen et al. (2004)) established differences in productivity of up to 40% between operators. In a log-by-log productivity analysis in Australian radiata pine plantations, Alam et al. (2014) established that differences between two similar harvesters were due to operators' technique. Moreover, other researchers have acknowledged the effect of operators when developing productivity models without quantifying it (Arlinger et al., 2014; Spinelli et al., 2010).

No clear pattern existed for processing and effective work time amongst the operators with the proportion of time varying from 62% to 79%, and 68% to 85%, respectively (Table 3).

Slope and shift effect

The integration of a GNSS receiver enabled the analysis of a slope effect on harvester productivity. In this study, slope did not have a significant effect, probably because the study area only included slopes up to 12%, which did not limit a wheeled harvester. In addition, the DTM resolution of 30 m may have had small areas of steep slope that were no detected at this resolution. Many studies that evaluated the effect of slope on productivity of wheeled harvesters working in *Eucalyptus* spp. plantations arrived at a similar conclusion. These studies found that productivity was only affected at slopes over 20% (Fernandes et al., 2013; Leite et al., 2014).Leite et al. (2013) developed a model in Brazil studying a continuous range of slopes from 0% to 70% and established that the effect of slope on harvester productivity started at 17% or 25% slope depending on whether the machine was working uphill or downhill, respectively. Simões et al. (2010) however, found a consistent decrease in productivity for a range of slopes from 10% to 25% for a tracked harvester. Therefore, the methodology of cross analysing a DTM and stem data is still a valid approach. Further research should use this approach to contrast productivity on sites with steeper slopes.

Productivity did not differ significantly between day and night shifts, which concurs with a recent study of processor's performance in New Zealand harvesting operations (Murphy et al., 2014). It should be noted that the night shift was two hours shorter than the day shift and both had an hour included for a meal break.

Efficiency

The combined use of stm and drf files allowed us to isolate processing time defined as "harvesting head and linkage active" (Arlinger et al., 2011). This included not only felling, delimbing, debarking and cross cutting, but also other activities such as brushing, moving residue, and head positioning. In CTL clear-cut operations, these other activities can account for 13% to 33% of the total processing time (Burla, 2008; Nurminen et al., 2006; Spinelli et al., 2002).

The proportions of effective work time (Utilization) of 75% to 84% from the current study (Table 3) were comparable to those from other long-term studies (Table 7). These studies however were based on PMH15 or delay free PMH, whereas our study used PMH03; therefore, comparisons should be considered with care.

Table 7: Efficiencies references from other long-term studies.

Publication source	**Base time**	**Number of harvesters**	**Time covered by the study**	**Source of data**	**Average (range) (%)**
Eriksson et al. (2014)	PMH15	423	3 years	Company's records	78
Spinelli and Visser (2008)	Delay free PMH	34	692 hours	34 time studies	71 (49-90)
Silva (2011)	Short delays included	2	6 months	Company's records	80 (74-85)
Linhares et al. (2012)	PMH non specified	4	1 years	Company's records	76
Holzleitner et al. (2011)	PMH15	12	4 years	Company's records	62 (28-95)
Silva et al. (2010)	PMH non specified	1	5 months	Company's records	78

The ratio of processing time over effective work time (Table 3) was between 90% and 93% for the range of species and ages, which concurs with what Nurminen et al. (2006) reported for a study in Finland (81% to 93%). Conversely, our findings are considerably higher than the ratio of 17% to 45%

reported by Gerasimov et al. (2012) for harvesters in the northern European part of Russia working in mixed species stands. Those authors recognized their values as very low. In our study, sites were even-aged, single species and first rotation stands and 100% of the production were pulpwood at a single length, which made the conditions more favourable. In addition, the harvester was a relatively new machine (3080 hours at the beginning of the study), so high utilization rates would be expected.

General comments

By developing a mixed-effects model, productivity equations to predict harvester productivity as a function of DBH for each species and individual equations for operators were created. These constitute the first models developed for predicting harvesters' productivity in *Eucalyptus* spp. plantations in Uruguay. The company managing the harvesting operations could use the latter for operators' performance management; namely, to calculate pay rates and set incentives, performance assessment, training, etc. Furthermore, given the high level of adoption of harvesters for harvesting forest plantations in South America, this work sets the foundation to develop further research to take advantage of StanForD files in South American countries.

Although it has some limitations, it has been reinforced the convenience of using data automatically collected by harvesters. Raw data from normal operations (stm and drf files) was used to prove it could be used as a tool to evaluate productivity at any time as long as stm files were being recorded and the quality of data was reliable; i.e. regular calibration and maintenance, operator training, etc. Moreover, the effect of many variables were analysed, namely species, operator, shift and slope. It was also proved the GNSS addition to the harvester to be a promising source of data to run overlay analysis using digital information from the environment (e.g. topographic maps) in a GIS application. This provides new opportunities for analysing data across extensive areas since the automatic data collection does not incur additional direct costs. In addition, for more detailed studies that aim to identify specific components of the cycle (processing, positioning, etc.), the analysis of StanForD data can be the first step to identify critical factors. Subsequent manual study can then be used to understand or isolate specific points of interest such as: determining the approaches/techniques used by operators that drive differences in productivity; determining where in the landscape the terrain causes productivity limitations; how the productivity varies along a shift or day, and more.

Downloading the StanForD files into a spreadsheet, rather than using specific software developed by a manufacturer, has advantages that include the practitioner not being limited to the capabilities of specific software. It is therefore possible to use data from various manufacturers (control systems) that comply with StanForD and access all the information contained in the files.

The presence of outliers in the dataset (Figure 6) is common in operational data records since the system automatically captures data with its sensors; for instance a tree that is dropped in the middle of processing and picked up again can be recorded twice, and the associated processing time calculated has these types of errors. I believe from my experience however, that these outliers were balanced, as can be seen in the graph shown in Figure 6. There were outliers for low DBH and very high productivity, large DBH and very low productivity, and large DBH and very high productivity.

As GNSS enabled stm files contain data and geospatial location for each individual stem (Figure 4), further research should take advantage of the use of this forest information (DBH, commercial volume, total harvested volume, assortments, values, commercial height, diameter sections each 10cm along the stem, harvest unit) to evaluate forest characteristics. Forest productivity maps, site index studies, overlay analysis with soil and topographic maps and taper functions are examples of the potential use of this source of data and some of the techniques used in this work.

Harvester productivity assessments in Uruguay can be expanded to more companies, machine makers, locations, slope classes and operators to enrich the developed model.

CONCLUSIONS

Operator, DBH, and species significantly affected the performance of the harvester working in *Eucalyptus* spp. plantations in Uruguay. Slope and shift, on the other hand did not significantly affect its performance.

GNSS-enabled data automatically collected by harvesters recorded as stm files made it possible to evaluate machine productivity due to both the coordinates and the time stamp records at felling time, which allowed us to overlay them with slope maps using GIS software.

The drf files made it possible to exclude all records from stm files that had a delay or anything other than processing time on them.

APPENDIX

Models 1 and 4 information, R script codes, variables classification, coefficients and statistics.

Model 1

R code: a <- lme(ln (productivity) ~ ln (DBH) + shift + species + slope_class + ln (DBH):species + ln (DBH):slope_class, random = ~1 | operator, data = hvp.model, method = "ML")

Random effects: Operator

Fixed effects: ln (productivity) ~ ln (DBH) + shift + species + slope_class

Interactions: ln (DBH):species + ln (DBH):slope class

n = 42478

	Value	Std. Error	DF	t-value	p-value
(Intercept)	-8.693893	0.110739	42465	-78.5080	0
ln(DBH)	2.242890	0.017446	42465	128.5613	0
shift Night	-0.006251	0.005623	42465	-1.1116	0.2663
species *E. dunnii*	-0.672682	0.118218	42465	-5.6902	0
species *E. grandis*	-1.326371	0.131605	42465	-10.0785	0
species *E. maidenii*	-0.381114	0.104727	42465	-3.6391	0.0003
slope_class 6.1 - 12%	0.256976	0.156210	42465	1.6451	0.1
ln (DBH):species *E. dunnii*	0.137162	0.022678	42465	6.0484	0
ln (DBH):species *E. grandis*	0.251252	0.025392	42465	9.8951	0
ln (DBH):species *E. maidenii*	0.087181	0.020225	42465	4.3105	0
ln (DBH):slope_class 6.1 - 12%	-0.048241	0.030504	42465	-1.5815	0.1138

Model 4

R code: a <- lme(ln (productivity) ~ ln (DBH) + species + ln (DBH):species, random = ~1 | operator, data = hvp.model, method = "ML")

Random effects: Operator

Fixed effects: ln (productivity) ~ ln (DBH) + species

Interactions: ln (DBH):species

n = 42478

	Value	Std. Error	DF	t-value	p-value
(Intercept)	-8.678301	0.109891	42468	-78.9721	0
ln (DBH)	2.239237	0.017229	42468	129.9702	0
species *E. dunnii*	-0.679114	0.118045	42468	-5.7530	0
species *E. grandis*	-1.343430	0.131009	42468	-10.2545	0
species *E. maidenii*	-0.380445	0.104458	42468	-3.6421	3.0×10^{-4}
ln (DBH):species *E. dunnii*	0.138464	0.022638	42468	6.1164	0
ln (DBH):species *E. grandis*	0.254599	0.025265	42468	10.0772	0
ln (DBH):species *E. maidenii*	0.087253	0.020166	42468	4.3267	0

Chapter 3: Forest yield maps from GNSS-enabled harvester StanForD files: preliminary concepts

The contents of this chapter have been published as:

Olivera, A., & Visser, R. (2016). *Development of forest-yield maps generated from global navigation satellite system (GNSS) enabled harvester StanForD files: preliminary concepts*. New Zealand Journal of Forestry Science. DOI: 10.1186/s40490-016-0059-x

ABSTRACT

The productivity of fast-growing forest plantation stands varies across short distances depending on site and forest characteristics. This indicates that forest managers would benefit from a site-specific approach to forest management. One tool used to characterise such productivity variations is in the form of yield maps, and a cost-effective source of data for these maps is automatically collected by harvesters. In order to generate such maps, it is necessary to understand the effect of geospatial accuracy of tree location recorded by the harvester.

This study investigated data sets from four stands, and sub-metre accurate tree location was available for two of these. The tree-location data for the remaining two sites were collected by a harvester and contained some inaccuracies associated with the Global Navigation Satellite System (GNSS) recording when under forest canopy and the physical dislocation of the GNSS. The GNSS unit is on the cabin of the machine, but the tree is felled using a boom and could be up to 12 metres from the cabin.

A suitable spatial resolution for studying variations in stand productivity mean tree volume and stocking across stands was established that enabled the development of useful forest yield maps from harvester data.

By assessing variability in volume per hectare, stocking rate, and mean tree volume across a range of cell sizes from 10 x 10 m to 100 x 100 m, we conclude that a cell length between 30 and 40 m is suitable for use as a reference when calculating volume per hectare and mean stem volume, while a 60 m long cell is more suitable for evaluating stocking density. The variability pattern is consistent for the various accuracy levels. When the known positions of trees are relatively inaccurate, using mean tree volume and stocking rate per cell might be a method for mapping productivity from harvester data.

Key words: harvester data, forest yield map, *Eucalyptus*, Uruguay

INTRODUCTION

The length of rotation of fast-growing *Eucalyptus* spp. plantations in many South American countries has been reduced as a result of intensive breeding programmes and improvements in silvicultural practices. For example, rotation ages of 6-8 years and 9-12 years have been achieved in Brazil and Uruguay respectively for pulpwood plantations (Andreoni and Bussoni, 2014; Gonçalves et al., 2013). This type of forest management is intensive in the use of agrochemicals (fertilisers, herbicides) and operations (agrochemical applications, soil preparation) during the establishment phase. Similar to agricultural crops, forest productivity also varies across short distances depending on both site (soil properties and topography) and forest (genotype, stocking rate, silvicultural practices, etc.) characteristics.

The concept of site-specific management aims to acknowledge site variability and adjust silvicultural practices accordingly, instead of managing stands based on average stand characteristics, which is the prevalent approach for forest plantation management at present. A number of authors based on intensive sampling have quantified within-stand variability (i.e. over short distances). Using Site Index (SI) as a productivity potential indicator, Ortiz et al. (2006) mapped and related the variability of productivity to soil properties and relief for a 6.3 ha stand of *Eucalyptus grandis* W. Hill clones in Sao Paulo, Brazil. They used 41 sample plots to assess this stand, and found significant correlations for productivity with six soil properties and also with elevation. Barbosa et al. (2012) reported a significant effect of soil pH on the productivity of a 3 ha stand of *Pinus caribaea* var. *hondurensis* (Sénécl.) W.H.Barrett & Golfari in the state of Mato Grosso do Sul, Brazil following extensive mapping using a grid of 121 points. A 3.6 ha stand of *Pinus taeda* L. located in Auburn, Alabama, USA was divided into four separate management zones based on a survey of the variation in stocking and productivity across the stand (Brodbeck et al., 2007). These results indicate that forest management in general would benefit from a site-specific management approach to make the process more efficient while reducing costs and environmental impact. In addition, several other researchers have used different study techniques to assess site variability and have proven, or at least pointed out, the viability of the site-specific management approach (du Toit et al., 2010; Gonçalves et al., 2012; González Barrios et al., 2015; Vergara, 2004). The adoption of site-specific management has some limitations, however. For example, the assessment of variation in soil properties and other forest variables through intensive sampling would be prohibitively expensive for large areas. In addition, forest managers would expect to see clear benefits in production before considering implementation of the additional complexity this approach requires.

In the context of site-specific management, forest-productivity maps are a useful resource to quantify and qualify variations across forested areas. Several techniques have been used to develop forest-yield maps based on plot samples (Mello et al., 2005; Mello et al., 2009; Ortega et al., 2002), a combination of plots and Light Detection and Ranging (LiDAR) (Chen and Zhu, 2012; Rombouts et al., 2010), LiDAR solely when stand age is known, variables derived from satellite imagery combined with environmental surfaces (Watt et al., 2015), and tree surveys (Brodbeck et al., 2007). A promising and cost-effective source of data for mapping productivity is data automatically collected by harvesters when trees are felled and processed. This topic has been discussed and its benefits explored for forestry plantations (Taylor et al., 2006), but it is yet to be developed.

Productivity maps based on harvester data are used in agriculture. The concept behind the usefulness of yield maps is to evaluate the variation in productivity across the area based on its real harvested production. Having this information at hand provides practitioners with useful information to manage sites specifically according to their characteristics (topography, soil, water availability, fertility, etc.) and creates potential for improving profitability and reducing environmental impact through more targeted applications of fertilisers and or pesticides. The required equipment for collecting data for mapping productivity is a harvester equipped with a yield sensor (determined using either mass flow or volumetric methodology) and a Global Navigation Satellite System (GNSS), preferably with a differential correction system to improve accuracy. (Bongiovanni and Lowenberg-DeBoer, 2006; Griffin, 2010; Zhang et al., 2002)

Similar to agricultural harvesters, modern forest harvesters are equipped with a standard software system (StanForD) to automatically record data during the harvesting operation. Developed in Scandinavia in 1988, StanForD is now used in many countries (Skogforsk, 2015), becoming a *de facto* standard. Harvesters that comply with this standard have been widely adopted in harvesting operations in Uruguay, Brazil and Chile. In Uruguay, although there are no official data available, it is estimated that over 60% of the 12 million cubic metres of forest harvested each year use harvesters (MGAP, 2015). Hence, there is a substantial potential to use the data collected in these countries as an input into site-specific management plans.

StanForD produces more than 20 types of files that record data from the harvesting operation and the forest, including .pri (production individual files) and .stm (individual stem data) (Skogforsk, as cited in Olivera et al. (2014)). These files can be used by forestry companies and contractors to manage various aspects of production, and have been used in numerous research applications (Olivera et al., 2015). Stem files (.stm) compress data for each individual harvested tree, including: stem identification number; diameter at breast height (DBH); diameter sections measured at 10 cm intervals along the stem; stem volume; individual log volume; and log classification. Moreover, when harvesters are equipped with a GNSS receiver, geographic coordinates of each tree at felling time are included in the files. Stem (.stm) files also contain manually inputted information such as species and site identification.

The data collection outputs of agricultural harvesters are different from forest harvesters. The results of data collected by agricultural harvesters may be provided in terms of mass (tons or kg) per unit of area (hectares, acres) (Bragachini et al., 2006; Griffin, 2010; Whelan and Taylor, 2013). Yield maps can be generated by removing points of erroneous yield estimations (caused by harvester turns and overlaps, narrow finishes, machine speed, GNSS positional errors, and empty spaces or voids) and interpolating productivity values from the original machine records (Lyle et al., 2014; Robinson and Metternicht, 2005). Forest harvesters, on the other hand, do not output units of volume per hectare; instead, they record individual tree data and a spatial location. These types of data are subject to two sources of error regarding to the spatial location:

a) *GNSS location*. The GNSS is typically mounted in the cabin of the machine but the tree is felled by the harvester head, which is mounted at the end of a boom that can be up to 12 m long. Therefore, the location of the tree will be incorrectly defined by a distance equivalent to the extension of the boom.

b) *GNSS accuracy*. The accuracy of commonly used grades of GNSS locators operated in similar conditions (i.e. forest environment with partial sky coverage) averages between 3 and 6 m with standard deviations up to 12 m (Veal et al., 2001; Wing, 2008; Wing et al., 2005; Yoshimura and Hasegawa, 2003). Moreover, using devices capable of use GPS and GLONASS satellites for positioning, (Kaartinen et al., 2015) determined and accuracy ranging between 4 and 9m. These errors make accurately evaluating the distribution of volume and stocking per hectare a challenging task.

Therefore, prior to developing productivity maps from GNSS-enabled harvester data, it is necessary to establish a spatial resolution that can overcome the limitations in tree accuracy location from this type of data. The overall objectives of this study are to improve our understanding of spatial resolution for studying variations in volume and stocking across forested stands, and to establish guidelines for actual spatial resolution that would allow the development of fit-for-purpose forest yield maps from harvester data.

MATERIALS AND METHODS

Study sites

Seven sets of data comprising information on individual trees were collected/generated. Stand 1 is a 3.6 ha area planted on a 15% slope site located 9.6 km north of Auburn, Alabama, USA. At the data collection time (pre-2007) the stand was 25 years and was thinned at the age of 16 (Table 8). The position of each *Pinus taeda* tree within the stand was measured with sub-centimetre accuracy as described in Brodbeck et al. (2007). The information contained in this dataset was: tree identity; latitude, longitude and altitude above sea level (X, Y and Z coordinates respectively); and DBH. With this information, height and volume of each tree was calculated using the same equations for pulpwood described by Brodbeck et al. (2007) shown as Equations 3 and 4 respectively.

$$\textit{Height (m)} = 12.689 + 0.253 * \text{DBH} \tag{3}$$

$$\textit{Volume (m}^3\textit{)} = 0.23233 * \text{DBH}^2 * \text{height} \tag{4}$$

For both equations, DBH is in cm.

Stand 2 was artificially generated using ArcGIS 10.2.2 software (Esri Inc., 2014a) for a stand of 6.65 ha. Initial tree spacing was uniform with 3.5 m between rows and 2.15 m between trees in the same row, resulting in a theoretical stocking of 1328 trees ha^{-1}. This was randomly reduced by 27% to 967 trees ha^{-1} to simulate a typical level of mortality. Tree volumes were defined using an independent dataset from .stm records from a stand planted with *E. dunnii*. In addition, individual tree volume was increased in the direction northeast to southwest, to deliberately create a spatial trend in stand volume variation.

Stands 3 to 7 are all even-aged, first-rotation forest plantations located in the northern part of the Rio Negro department in Uruguay. The original spacing of these five stands were equal to the spacing used to generate Stand 2; the average stocking at harvesting time varied between 794 and 994 trees ha^{-1}. Stands 3 and 7 contained *E. dunnii*; Stand 4 was comprised of *E. maidenii*; while *E. bicostata* and *E. grandis* were planted in Stands 5 and 6 respectively. Records relating to the trees in Stands 3 to 7 were obtained from .stm files acquired using a single-grip harvester Ponsse Ergo 8W equipped with a combined GSM-GNSS antenna fitted on the cabin for geospatial data collection and communication. The control system used was Opti4G 4.715 (Ponsse Oyj, nd.), which complies with the StanForD standard. All harvested trees were debarked and cross-cut for pulpwood logs. Further details of each stand are provided in Table 8. The analysis variables are: volume per hectare (m^3 ha^{-1}); stocking (trees ha^{-1}); and mean tree volume (m^3).

Data for Stands 1 and 2 were used to study the variability of these three variables. The results of Stands 1 and 2 where then compared with Stands 3 to 7 to verify if there are differences in pattern attributed to the accuracy of tree records.

Table 8: Characteristics of the seven studied stands

	Stand 1	Stand 2	Stand 3	Stand 4	Stand 5	Stand 6	Stand 7
Location	32°41’43”N, 85°30’11”W	--	32°33’18”S, 57°24’19”W	32°32’41”S, 57°24’04”W	32°31’52”S, 57°22’52”W	32°34’40”S, 57°23’28”W	32°34’46”S, 57°23’07”W
Species	*P. taeda* [a]	--	*E. dunnii* [b]	*E. maidenii* [c]	*E. bicostata* [d]	*E. grandis* [e]	*E. dunnii* [b]
Age (years)	25	--	19	19	19	16	16
Year of data collection	Pre-2007	--	2014	2014	2014	2014	2014
Area (ha)	3.6	6.65	6.65	8.05	6.65	4.08	6.97
Average stocking rate (n° trees ha^{-1})	661	967	967	899	994	826	794
Thinned	at age 16	no	no	no	no	ND	ND
Volume studied [f]	Total volume	Merc. volume	Merc. volume	Merc. volume	Merc. volume	Merc. volume	Merc. volume
Average volume m^3ha^{-1}	157	506	464	213	339	290	230
Mean stem volume (m^3)	0.24	0.52	0.48	0.24	0.34	0.35	0.31

Note: [a] *Pinus taeda* (L.), [b] *Eucalyptus dunnii* (Maiden); [c] *Eucalyptus maidenii* (F.Muell); [d] *Eucalyptus bicostata*, (Maiden, Blakely & Simmons); [e] *Eucalyptus grandis* (W.Hill). ND: No data available. [f] Merc. (Merchantable) volume refers to volume of commercial logs only.

Cell size analysis

A map showing productivity variation across a stand can be generated directly using the position of each tree by dividing the stand area into cells of equal size and summing the volume of all trees within each cell. To determine a suitable cell size for productivity mapping, a cell-size analysis was carried out by dividing each stand in square cells of increasing length: 10 m; 20 m; 30 m; 40 m; 60 m; and 100 m (Figure 11).

The cell size analysis was done in two steps. Firstly, the tool Point to Raster in ArcGIS 10.2.2 (Esri Inc., 2014a) was used, which converts a point vector layer (stem records) into a raster layer giving the value of a single variable to each cell. This step was repeated for each combination of variable (3) cell size (6) and stand (7) (126 times). The second step was to analyse this information using Excel software (Microsoft Corporation, USA). This analysis assessed how the coefficient of variation (CV) of each variable changed as the cell size increased within the stand.

RESULTS AND DISCUSSION

The position of each tree in Stand 1 was measured empirically with high accuracy and the position of each tree in Stand 2 was generated artificially so that it was also accurately documented. Tree position in the remaining 5 stands (3 to 7) had a much lower level of geospatial accuracy because the data were collected indirectly by a harvester. The difference between surveyed or artificially generated stand data and harvester data can be readily seen in Figure 10. Maps of Stands 1 and 2 clearly show the trees in planted rows. In contrast, the maps of Stands 3 and 4 show the path of the harvester as the trees are felled in addition to the two sources of location error outlined above. Records of Stands 5 to 7 showed a similar pattern to Stands 3 and 4.

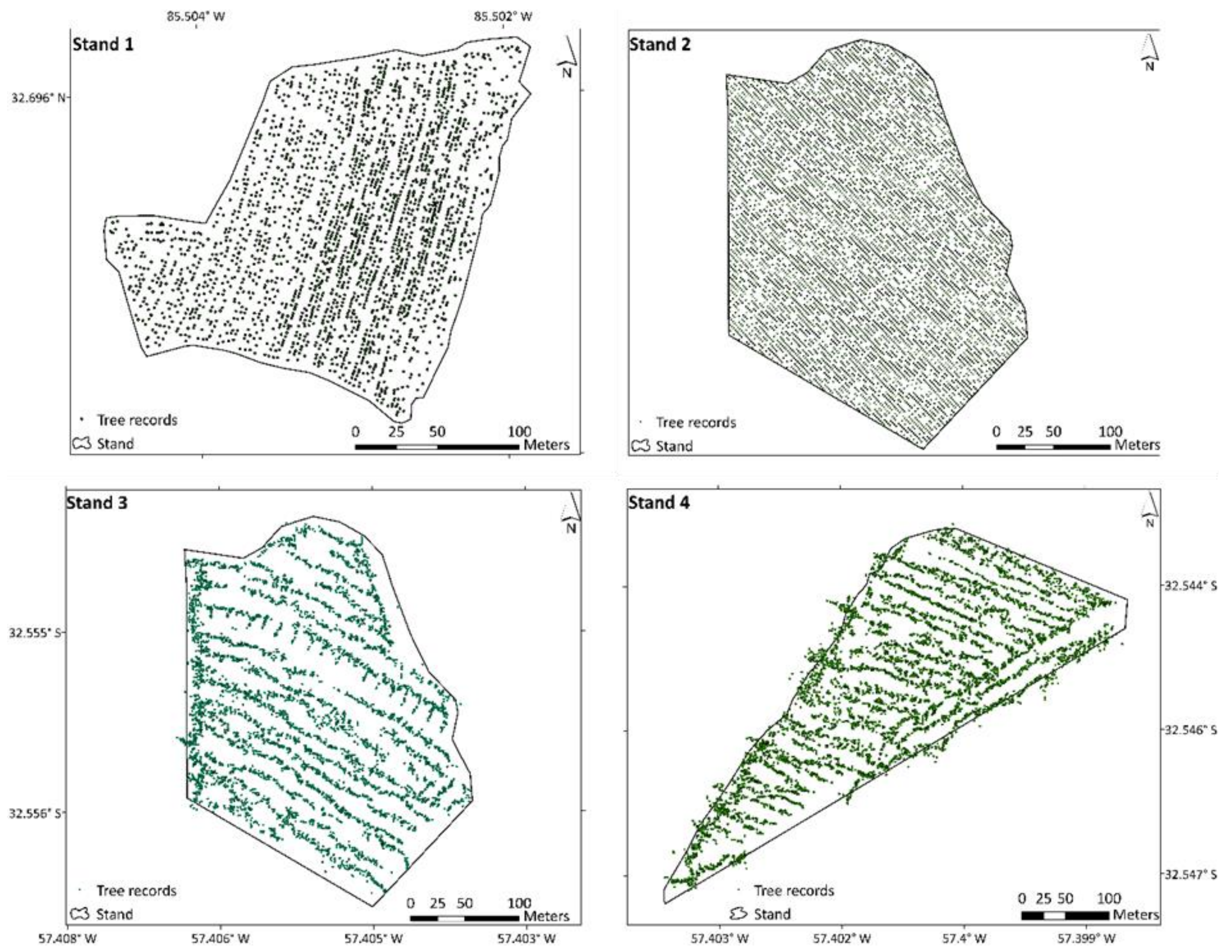

Figure 10: Maps of Stands 1 to 4 with details of location and tree records pattern. Stand 1 has accurate tree location and uneven stocking, artificially generated Stand 2 has accurate tree location and even stocking, and Stands 3 and 4 are plotted from stm files. Stands 5 to 7 are not included as they present similar pattern to Stands 3 and 4.

Cell size distribution

The results of the cell-size analysis for the three variables showed that the CV is expected to decrease as cell size increases, until it reaches the size and the overall average of the stand. It is expected that the CV will stabilise, which indicates that the variability due to cell size is small and the remaining variability is from the stand itself.

Volume per hectare and stocking per hectare were calculated only from cells that were completely within the boundaries of Stands 1 and 2 (Figure 11 shows Stand 1 as example). This approach was used because these variables are related to the total cell area and are expressed per hectare. Mean stem volume from cells of 20 to 100 m in length was calculated using data from all cells containing 30 or more stem records, even though they may have fallen partially outside the stand boundary. The number of cells included from each stand for each variable is shown in Table 9. As the cell size increased the proportion of useable cells for calculating volume and stocking decreased because of the increasing number of cells that fall partially outside of the stand (Figure 11). Conversely, the proportion of useable cells for calculating mean stem volume was stable for all cell sizes.

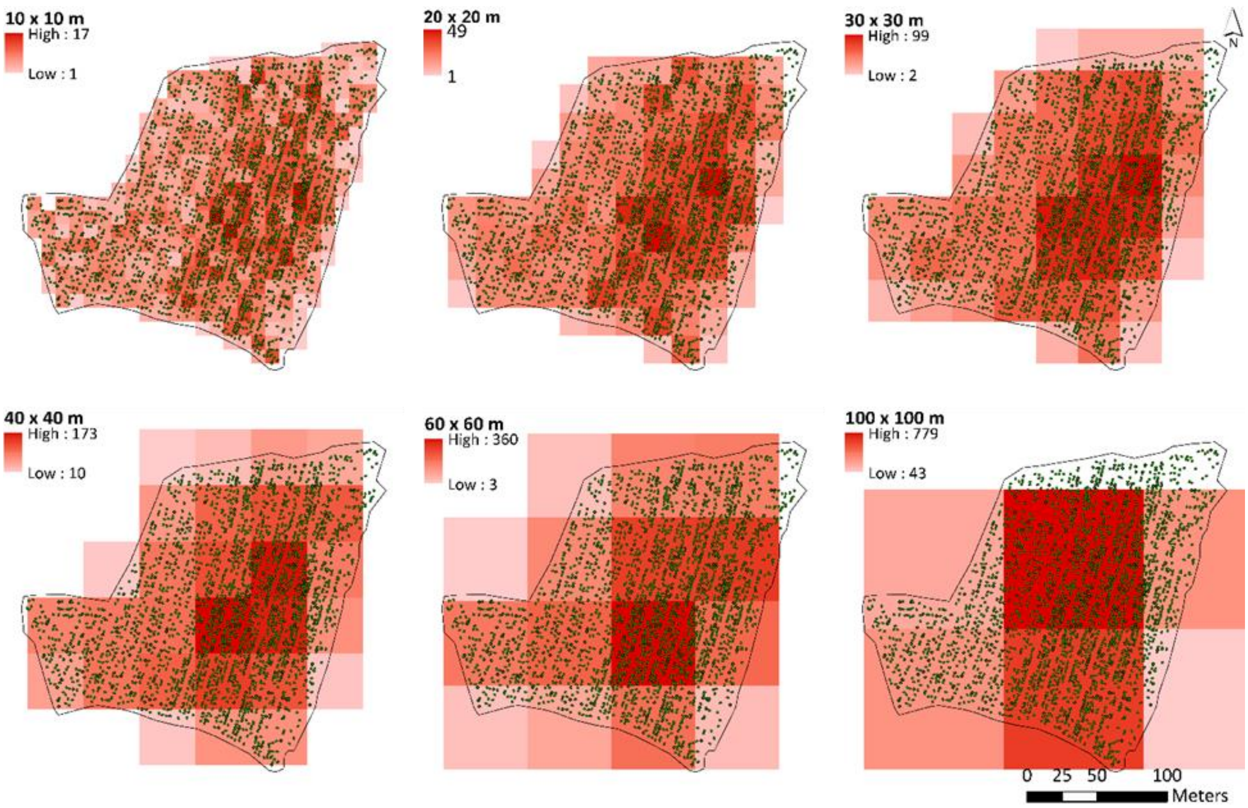

Figure 11: Detail of Stand 1 divided in six cell sizes as indicated in each map. Values refer to the range of number of trees per cell.

Table 9: Detail of cell divisions for the seven stands and six cell sizes.

	Cell size (m)	10	20	30	40	60	100
Stand 1	Number of cells	359	103	52	29	15	6
	Number of cells - no edges	311	67	27	13	3	1
	Number of empty cells	1	0	0	0	0	0
	Cells used for mean volume calculation	311	63	34	24	15	6
Stand 2	Number of cells	699	188	88	53	23	11
	Number of cells - no edges	621	146	58	32	11	3
	Number of empty cells	0	0	0	0	0	0
	Cells used for mean volume calculation	621	161	76	47	22	11
Stand 3	Number of cells	562	174	83	51	22	9
	Number of cells - no edges	551	166	68	39	14	4
	Number of empty cells	72	2	0	0	0	0
	Cells used for mean volume calculation	562	166	75	47	22	9
Stand 4	Number of cells	791	241	122	75	36	15
	Number of cells - no edges	791	207	71	33	14	4
	Number of empty cells	93	2	0	0	0	0
	Cells used for mean volume calculation	791	207	95	58	33	13
Stand 5	Number of cells	630	200	99	60	31	15
	Number of cells - no edges	573	167	59	29	12	2
	Number of empty cells	84	0	0	0	0	0
	Cells used for mean volume calculation	573	167	79	50	28	14
Stand 6	Number of cells	355	122	62	39	21	12
	Number of cells - no edges	334	102	32	15	6	2
	Number of empty cells	63	0	0	0	0	0
	Cells used for mean volume calculation	334	102	50	32	18	9
Stand 7	Number of cells	628	220	114	73	41	17
	Number of cells - no edges	520	170	52	28	11	0
	Number of empty cells	78	1	0	0	0	0
	Cells used for mean volume calculation	520	170	78	55	36	16

A large number of empty cells existed in Stands 3 and 4 when a cell length of 10 m was applied (Table 9). This is unlikely to represent reality because the area is a plantation forest without thinning and with gaps excluded by the company remapping executed in 2013 (Managers pers. Comm.), thus, there should be very few, if any, empty cells. For these two stands, there were also empty cells when the cell length was 20 m. When cell length was increased to either 60 or 100 m, the results were similar to those obtained for the overall average of the whole stand. Also, the number of cells that fell completely inside the stand decreased such that only one 100 m long cell fell completely within Stand 1 (Figure 11).

Volume per hectare

Increasing cell length only slightly affected the calculated average volume per hectare, with variation within ± 10% in the majority of cases (33 out of 40) (Table 10) compared with the empirical values (Table 8). However, as the cell length increased, the CV of volume per hectare decreased consistently for all stands independent of the type of data that was used (Figure 12 and Figure 13). However, the range of this CV as the cell size changed differed for the various stand types. Both stands that have accurate tree location (Stands 1 and 2) produced a lower CV at 10 m cell length (32 – 33%) than the harvester data stands (Stands 3 to 7) (67 – 77%)(Figure 13). The CV decreased when the cell length was increased to 20 m for all stands. The values of CV continued to decrease at similar rates when cell length increased to 30 m cell for Stands 3 to 7, but the decrease reached an asymptote for Stands 1 and 2. The CV decreased for all stands when the cell length increased from 30 m to 40 m. For all stands except 6 and 3 the value of CV stabilizes between 40 and 60 m cell length. This pattern of variation suggests that cell length contributes more to the overall variability in small (10 m to 20 m long) cells for Stands 1 and 2.

For harvester data, the contribution of cell size to the overall variability was up to 30 m long for Stands 4, 5 and 7, and up to 40 m long for Stands 3 and 6. For cells 40 m to 60 m long, the variability in productivity can be attributed to other causes from the environment or the forest such as soil characteristics, topography, stocking, and even tree location accuracy for Stands 1, 2, 4, 5 and 7; whereas for Stands 3 and 6 this assumption can be made at cell 60 m long. At 60 m cell length, however, the number of cells that fit in a small stand –Stand 1 for example– is reduced, resulting in a coarse resolution for further analysis of volume. For a 100 m cell length, the CV is the lowest for Stands 2 to 6 as the area of each cell represents more the average of the stand and the number of cells are reduced (Table 9).

As such, when tree locations are accurately recorded; using a cell length between 30 m and 40 m constitutes a reasonable unit size to subdivide a stand to study the volume variation (productivity) across its area. Whereas for harvester data the suitable cell size varies from 40 m (Stands 4, 5 and 7) to 60 m (Stands 3 and 6).

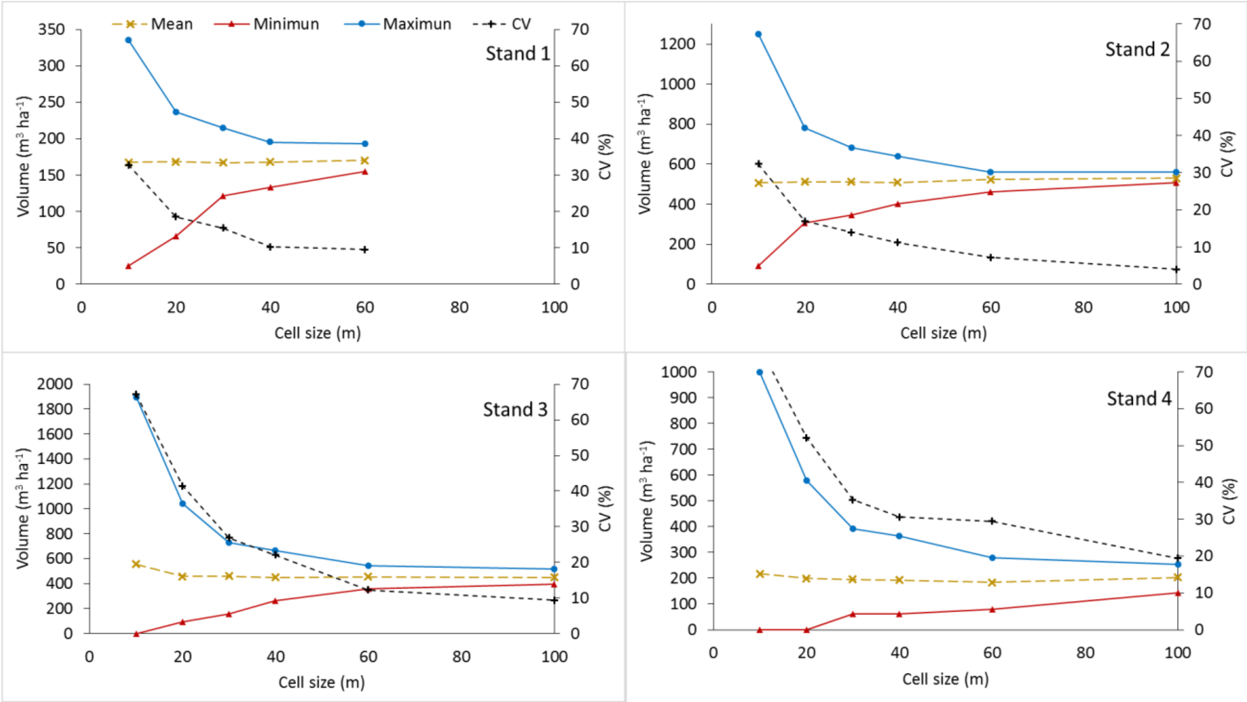

Figure 12: Changes in the range of volume per hectare and its coefficient of variation as cell size increases from 10 m to 100 m for Stands 1 to 4. No values for 100 m cell in Stand 1 because there is only one cell.

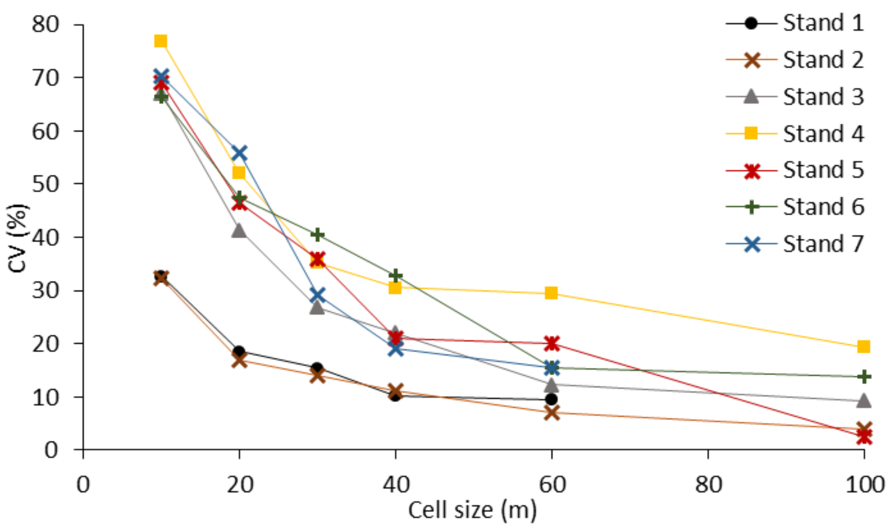

Figure 13: Changes in the coefficient of variation (CV) of volume per hectare for all stands as cell size increases from 10 m to 100 m.

Stocking

Coefficient of variation values of stocking for all stands followed a similar pattern as for volume, i.e. the CV diminished as cell size increased. Also, the calculated averages were stable for Stands 2 to 7, (Table 10, Figure 14, & Figure 15) and were similar to the overall empirical average (Table 8). For Stand 1, however, cells of all the lengths tested resulted in overestimation of the average stocking rate by 11 to 20% because the edges of the stand with lower stocking rates (Figure 10 and Figure 11) were excluded from the analysis because the cells that included these lower density edges were not fully within the stand.

Table 10: Average values of the three variables for each stand and each cell size.

	Cell size (m)	10	20	30	40	60	100
Stand 1	Volume per hectare (m^3)	168	169	167	168	170	--
	Stocking (stems ha^{-1})	733	760	770	793	792	--
	Mean stem volume (m^3)	0.26	0.25	0.25	0.25	0.26	0.26
Stand 2	Volume per hectare (m^3)	507	513	512	509	523	531
	Stocking (stems ha^{-1})	968	966	968	966	961	957
	Mean stem volume (m^3)	0.52	0.53	0.53	0.52	0.52	0.51
Stand 3	Volume per hectare (m^3)	556	459	462	450	455	451
	Stocking (stems ha^{-1})	1162	981	974	952	977	1006
	Mean stem volume (m^3)	0.50	0.48	0.48	0.48	0.47	0.45
Stand 4	Volume per hectare (m^3)	217	200	196	193	184	203
	Stocking (stems ha^{-1})	914	842	826	809	778	850
	Mean stem volume (m^3)	0.24	0.24	0.24	0.24	0.23	0.24
Stand 5	Volume per hectare (m^3)	376	321	310	307	318	297
	Stocking (stems ha^{-1})	1112	944	926	929	953	921
	Mean stem volume (m^3)	0.35	0.35	0.34	0.35	0.35	0.35
Stand 6	Volume per hectare (m^3)	346	271	263	270	259	288
	Stocking (stems ha^{-1})	984	803	780	777	748	819
	Mean stem volume (m^3)	0.38	0.36	0.35	0.35	0.35	0.35
Stand 7	Volume per hectare (m^3)	263	198	216	223	225	--
	Stocking (stems ha^{-1})	870	651	720	734	745	--
	Mean stem volume (m^3)	0.31	0.32	0.30	0.31	0.31	0.31

The variability of the stocking rate decreased rapidly when the cell length was increased from 10 m to 30 m for Stands 1 and 3 to 7, whereas for Stand 2 this rapid decease occurred in the transition from a 10 m to 20 m cell length. Low values of CV, ranging from 19 to 1%, across the different cell lengths in Stand 2 reflected the artificially generated even distribution of trees across this stand. A cell length 10 m (and even one of 20 m) does have an effect as reflected in the higher CV for these cell lengths. In the cases of Stands 1, 4 and 5 the CV fell as cell length increased from 10 m to 40 m then stabilised at a value around 21%. This result reflected the real variation in stocking rate across theses stands; variation that is clearly shown in Figure 10 and Figure 11 for Stands 1 and 4. The CV value for Stands 3, 6 and 7 decreased as cell length increased up to 60 m.

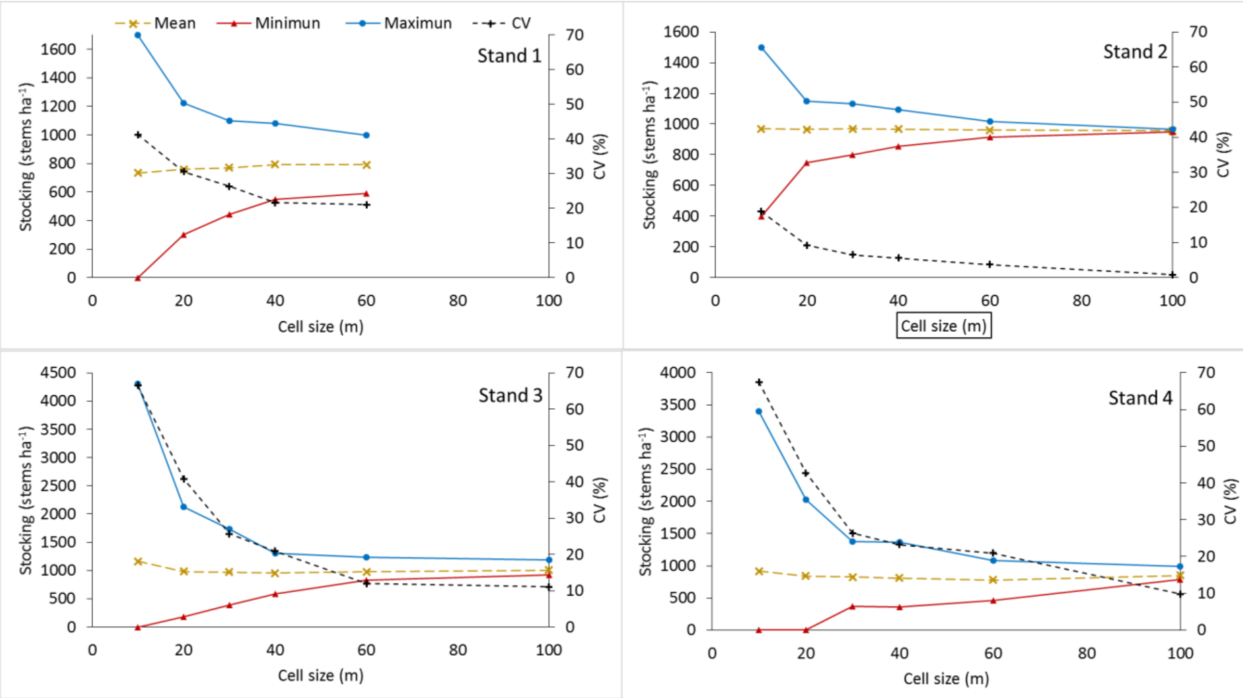

Figure 14: Changes in the range of stocking per hectare and its coefficient of variation as cell size increases from 10 m to 100 m for Stands 1 to 4. No values for 100 m cell in Stand 1 because there is only one cell.

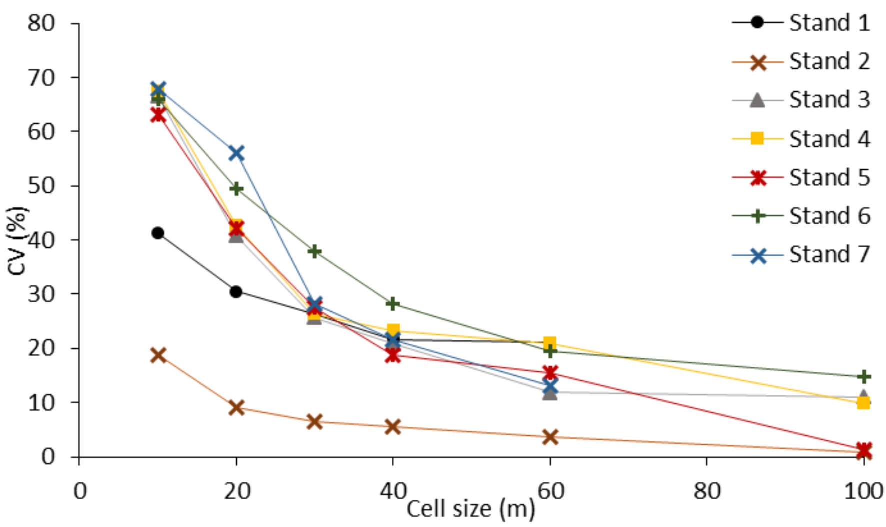

Figure 15: Changes in the coefficient of variation (CV) of stocking per hectare for all stands as cell size increases from 10 m to 100 m.

For Stand 1, which has accurate tree location and uneven stocking, the most suitable cell length for stocking rate analysis is 40 m to 60 m as the CV is stable over this range and suggests that the remaining variation (CV of 21%) is independent of cell size. For Stand 2, which has a homogeneous stocking density across the stand and accurate tree location, a cell length of 30 m or higher is suitable. If the distribution is not known *a priori* (as in the case of real stands using harvester data), however, working with 60 m cell length is a suitable option for mapping stocking levels, as was found for Stands 3, 6 and 7. For Stands 4 and 5, the CV was stable (20 – 26% and 15 to 19% respectively) for cells between 40 m and 60 m in length, suggesting that a cell size in this range would be suitable for stocking density analysis. The stable pattern for harvester data stands also shows that the errors in GNSS accuracy affecting the variability of the stocking rate may be negligible at this level of resolution.

Another important factor to consider is the size of the stand (or area evaluated). Stands smaller than 4 ha, such as Stand 1, would fit a very low number of 60 m long cells (Figure 11 and Table 9). This is not desirable if there is a variation in stocking across the stand. In this case, the use of 40 m long cells is advisable.

Mean tree volume

As with volume and stocking, mean tree volume varied considerably when 10 m long cells were used (Figure 16 and Figure 17). This variation decreased dramatically when cell length was increased to 20 m for Stands 1 to 6, to 30 m for Stand 7 and fell steadily as cell length increased up to 100 m. Variation was observed even with 100 m long cells, which suggests that there is an effect from the environment or the forest itself affecting stem mean volume in all seven stands. These results suggested a cell length between 20 m and 40 m (30 m and 40 m for Stand 7) would be suitable for further analysis. At smaller cell length, the high CV and low number of trees per cell would bias any analysis. Above 40 m length, the cell sizes are too large to capture any variation across the stand due to the large proportion of the stand each cell represents (Table 9).

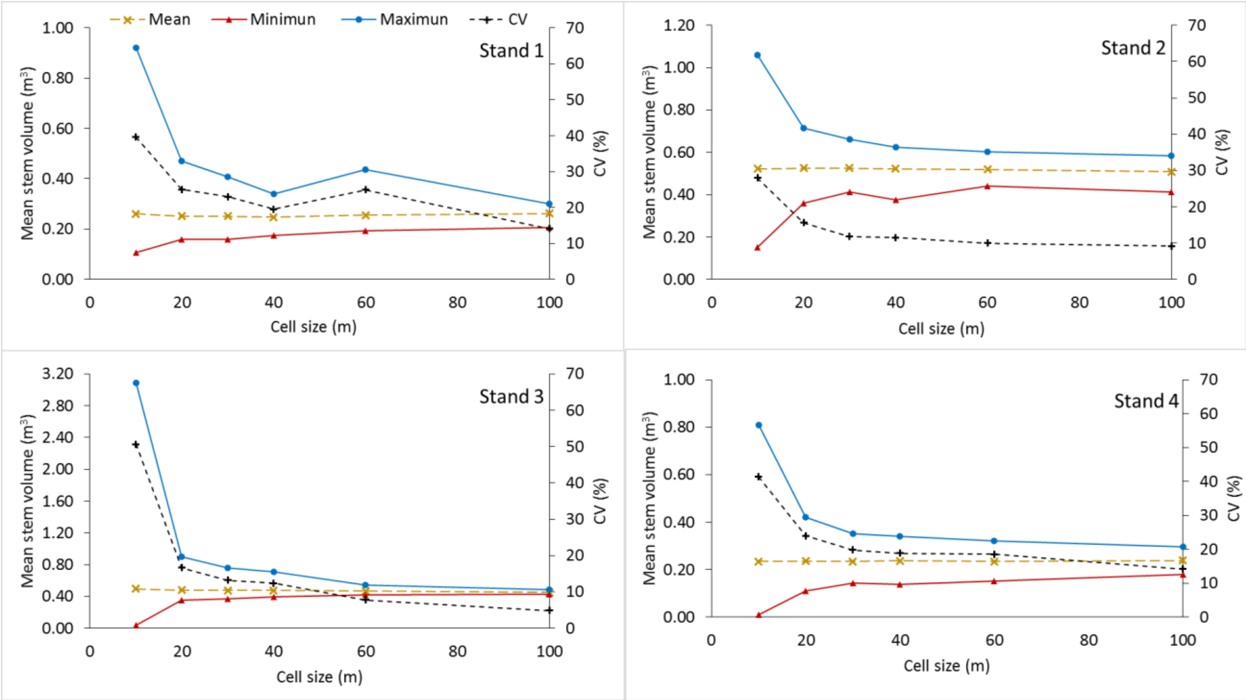

Figure 16: Changes in the range of mean stem volume and its coefficient of variation as cell size increases from 10 m to 100 m for Stands 1 to 4.

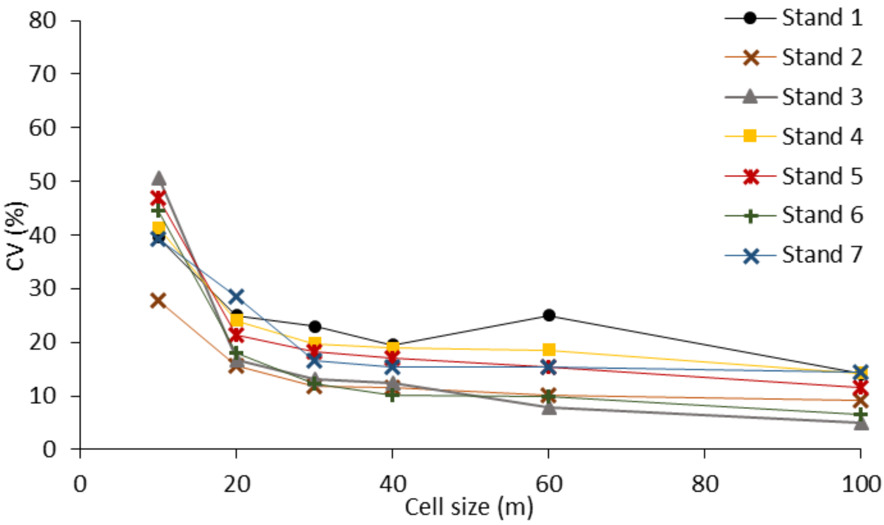

Figure 17: Changes in the coefficient of variation (CV) of mean tree volume for all stands as cell size increases from 10 m to 100 m.

CONCLUSIONS

Based on the changes in CV across the studied range of cell sizes, I conclude that a cell length between 40 and 60 m is suitable for use as a reference when estimating volume per hectare (productivity) and mean stem volume to further compare and develop the concepts of forest productivity maps. For evaluating stocking rate, the use of 60 m long cells is more suitable in situations where variation in stocking across an area is unknown, such us when using harvester data. For stands smaller than 4 ha, a 40 m long cell might be used to obtain a greater number of points. Nevertheless, the cell size to map productivity, stocking rate and mean tree volume must be assessed area-by-area using as criteria the cell size when the coefficient of variation stabilizes

The pattern of CV variation was consistent in both type of stands (accurate tree location and harvester data) for all three variables. However, there is still some uncertainty as to what proportion of the variation can be attributed to the environment and tree location accuracy for Stands 3 to 7. However, this study has shown that even if the position of trees is not accurate, using mean tree volume and stocking rate per cell can be a method for mapping productivity from harvester data. An idealised future study would fully survey all trees in a stand and then capture the corresponding harvester data set. This would allow a more complete understanding of what variation is attributable to the geospatial inaccuracy of the harvester versus the actual variation in the stand.

Chapter 4: Forest yield map from GNSS enabled harvester data: developing maps

The contents of this chapter have been prepared for publication:
Olivera, A., Visser, R., & Morgenroth, J. Forest yield map from GNSS enabled harvester data: developing maps (in prep)

ABSTRACT

To develop a method for mapping forest productivity using GNSS enabled harvester data, eight models were created using geostatistical techniques and applied to two model stands' data with accurate tree location. Seven models were based on the census of trees in the stands and one used pre-harvest inventory (PHI) plots only. The model's accuracy was then assessed by comparing the model-generated productivity maps with reference maps. The assessment criteria was a count of randomly generated points within ±5%, ±10% and ±20% of the reference maps which were used to assign a performance score out of a maximum of 100. Model performance scores varied from 25 to 74 for both stands.

The three most accurate models and the PHI model were selected and applied to harvester obtained data (Stem files) from five stands. The three models produced similar productivity maps for harvester data stands larger than 5 ha, while for a smaller stand they presented inconsistent results. The PHI model showed inconsistent results for all stands.

Productivity maps using the three selected models made it possible to map the variations in productivity stocking and mean tree volume in short distances for stands with accurate tree position location and for harvester data stands. Productivity maps from PHI plots with an intensity of one plot per hectare showed inconsistent results when compared with the three selected models.

Key words: forest productivity maps, StanForD, harvester data, *Eucalyptus* spp., Uruguay, Geostatistics.

INTRODUCTION

Modern forest harvesters capable of collecting georeferenced individual tree data have been used worldwide for more than two decades (Arlinger et al., 2007). While several opportunities from this technology have been explored for forest management and research (described in Chapters 1 and 2), new benefits can still be identified to make forest management processes more efficient. An opportunity not yet explored regarding the management of fast-growing forest plantations is the creation of productivity maps from data automatically collected by harvesters (Olivera et al., 2015; Taylor et al., 2006).

For research at sub-stand level, productivity maps have been created based on intensive sampling combined with the application of geostatistical methods (Barbosa et al., 2012; Ortiz, 2003), combining environmental surfaces and remote sensing technologies (Watt et al., 2015), and surveying all trees in a stand (Brodbeck et al., 2007). Intensive sampling is extremely costly to apply to forests in a larger scale. Furthermore, the use of inventory plots (with varying intensity), both alone or in combination with Light Detection and Ranging (LiDAR), makes the task of mapping productivity possible on large scales. In these situations, the acquisition of data has a cost and the capacity to capture the variability at a detailed level depends on the intensity of sampling. Intensive samples (several plots per hectare) for research projects have found significant variations within 60 to 120 m (Barbosa et al., 2012; Ortiz, 2003; Pereira et al., 2011), whereas using plot samples (one plot each several hectares) have quantified variations within 180 to 500 m (Mello et al., 2005; Mello et al., 2009). Therefore, as harvester data is a full census of all georeferenced trees (with some errors associated discussed in Chapter 3), rather than a sampling, it is much more likely that the variations in short distances are detected and better represented from a census. In addition, when trees are felled and processed with harvesters, which automatically collect this data, there are no direct costs for collecting data.

A forest yield map would therefore be a useful tool for research and decision making for subsequent rotations, based on data collected at harvesting time. A series of further opportunities arises to take advantage of forest yield maps, some already identified (Olivera et al., 2014). Based on a productivity map, areas with low and high productivity in a forest can be stratified. By stratifying the forest, the number of plots for inventories in the next rotation can be optimally placed in different strata because the variability across the area has already been evaluated. This would represent a gain in accuracy or predictions from inventory and potentially reduce the number of plots (Mello, 2004). The stratification also makes it possible to target site evaluations, such as soil sampling, in order to better understand forest productivity correlated to soil attributes and/or relief and manage the site specifically (Gonçalves et al., 2012; González Barrios et al., 2015; Ortiz et al., 2006; Vergara, 2004). Virtually any information available as digital layer data (Digital Terrain models, soil maps) can be overlaid to evaluate the factors affecting productivity. Moreover, when the wood volume and its variation across the area are known, correlated variables such as total biomass can be evaluated and mapped accurately (Möller et al., 2011).

Considering the whole forest process, the creation of detailed yield maps will complement the technology for site-specific management in silviculture of planted forest that is available in countries such as Brazil, Uruguay and the United States. Such technologies are based on technologies and equipment used in agriculture and adapted to forestry machines for silviculture. They include the use of GPS guidance and quality control in soil tillage; GPS controlled equipment for the application of herbicides in band or broad area; fertilization in bands, total area or localized; application of solid insecticides for ant control; and manual and mechanised plantation. The application of these technologies also includes the management of the information generated, for example application maps, initial assortment and plants localization, and quality control (McDonald et al., 2006; Taylor et al., 2002; Vieira et al., 2012).

Chapter 3 established a suitable resolution –expressed as cell size– for mapping productivity, stocking and mean tree volume for stands based on a census of all georeferenced trees. Such resolution must be evaluated for each stand; for the seven stands studied it varied from a 40 m to 60 m cell for productivity and stocking, and from a 30 m to 40 m cell for mean tree volume. The analysis of the variations in the coefficient of variation (CV) were similar for stands with accurate tree location and from harvester georeferenced data. This result suggests that the inaccuracies associated with the harvester data records are negligible at this cell size. Nevertheless, the exact influence of this factor is still unquantified.

Having established a suitable resolution to map productivity makes it possible to carry on and develop a method for mapping productivity from harvester data. The objective of this chapter is to develop such models to map productivity from harvester data based on the conclusions from Chapter 3, i.e. using two approaches: a) using the value of productivity (m^3 ha^{-1}) from a cell length of 40 to 60 m as the reference value for productivity; and b) multiplying mean tree volume by stocking per hectare. The hypothesis is that yield maps from harvester data can capture variations in small scale that maps from inventory plots, with an intensity of one plot of 300 m^2 per hectare, cannot (i.e. they produce more detailed productivity maps).

MATERIALS AND METHODS

Models for mapping productivity based on a census of georeferenced trees were developed using the Stands 1 and 2 data described in Chapter 3 (Table 8 and Figure 10). Seven productivity models were created; the accuracy of these models were assessed comparing the model generated maps with reference maps. The reference maps were generated dividing the area of each stand into 40 x 40 m cells and summing the volume of all trees within each cell. The selection of cell size is based on the findings of Chapter 3. Models 1 to 6 resulted from combining two approaches to group trees for averaging stem volume, and three methods to determine stocking. Model 7 was an interpolation of the centre point of each usable cell[1] (cell no edges in Table 9) of the reference map (Figure 18). Next, based on their performance for both stands, three models were selected and applied to five harvester data stands (Stands 3 to 7, Table 8).

The harvester data were obtained from .stm files from a single-grip harvester equipped with a combined GSM-GNSS antenna fitted on the cabin for geospatial data collection and communication. The harvester control system complied with the StanForD standard (Ponsse Oyj, 2009; Skogforsk, 2015). These five stands were even-aged, first rotation *Eucalyptus* spp. forest plantations located in the northern part of the Rio Negro department in Uruguay (Figure 2). All harvested production are debarked logs for pulpwood.

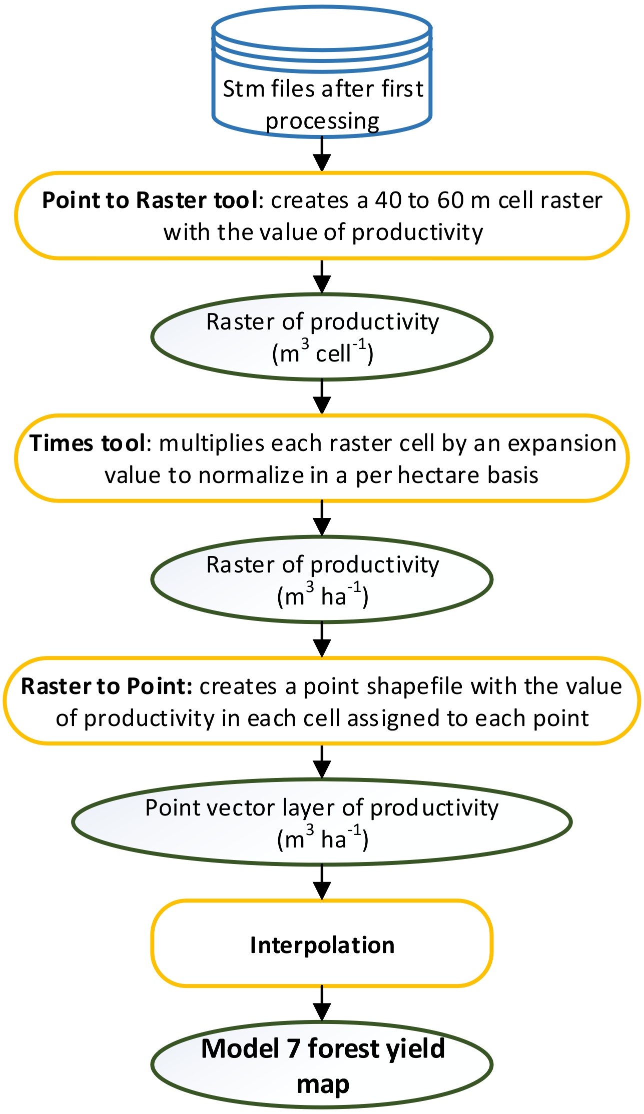

Figure 18: Diagram of Model 7 process, showing the sequence of steps. Blue box represents database, yellow boxes represent the ArcGIS tool used and green boxes represent layer data outputs

[1]Usable cell: cells that are completely within the boundaries of the stand when used to estimate productivity (m^3 ha^{-1}) and stocking (trees ha^{-1}); or cell that contain 30 or more three records when used to estimate mean tree volume.

Models

The six models using the variables mean stem volume and stocking (Models 1 to 6) were created in ArcGIS 10.2.2 (Esri Inc., 2014a). The models were formed from a factorial combination of two different methods for grouping trees to estimate mean tree volume; and three different methods for estimating stocking (Table 11).

Creating mean tree volume surfaces

Based on the conclusions of Chapter 3, a 40 m cell was used as a spatial unit for both tree-grouping methods (methods A and B). In method A, the stands were divided into square cells of 40 m in length using the tool Point to Raster that converts a point vector layer (stem records) into a raster layer giving the value of average tree volume to each cell (Figure 19). In method B, trees were grouped based on their X and Y coordinates using the tool Grouping Analysis; this tool has as input the number of groups the user defines. The groups contained on average the number of trees equivalent to a 40 m cell, as used in method A. For example, Stand 1 had 24 usable cells to calculate mean tree volume (Table 9), then method B would generate approximately 24 groups of contiguous trees (Table 12). Next, using the tool Mean Center, a new point with the average tree volume of each group located at the average X and Y coordinates of each group was created (Figure 20). The principal difference between both methods is that method A divides the area in cells that could result in a different number of trees per cell if the stocking changes across the area, which occurred in Stand 1. Method B on the other hand, maintained a consistent number of trees per group. Consequently, if the stocking varies across the area, each group will have a different area. The result of each method is a layer of data (raster for method A and point for method B) with the distribution of average tree volume across the stand (Table 11).

Table 11: Models 1 to 6 are a result from the combination of methods A (raster layer) and B (point vector layer) for grouping trees with method 1, 2 and 3 for determining stocking.

Model	Tree grouping method (layer format)	Stocking method
1	A (Raster layer)	1
2		2
3		3
4	B (Point vector layer)	1
5		2
6		3

Table 12: Detail of the number of 40 m cells from tree grouping methods A and B for determining average tree volume, and average number of trees for each stand. Stands 1 (field measured) and 2 (simulated) have accurate tree position, Stands 3 to 7 are from harvester data.

Grouping method	**A**		**B**	
	Nr. cells	**Trees/cell**	**Nr. groups**	**Trees/group**
Stand 1	24	98	24	93
Stand 2	47	135	45	143
Stand 3	47	136	50	129
Stand 4	58	121	60	121
Stand 5	50	130	55	120
Stand 6	32	118	35	96
Stand 7	55	90	49	113

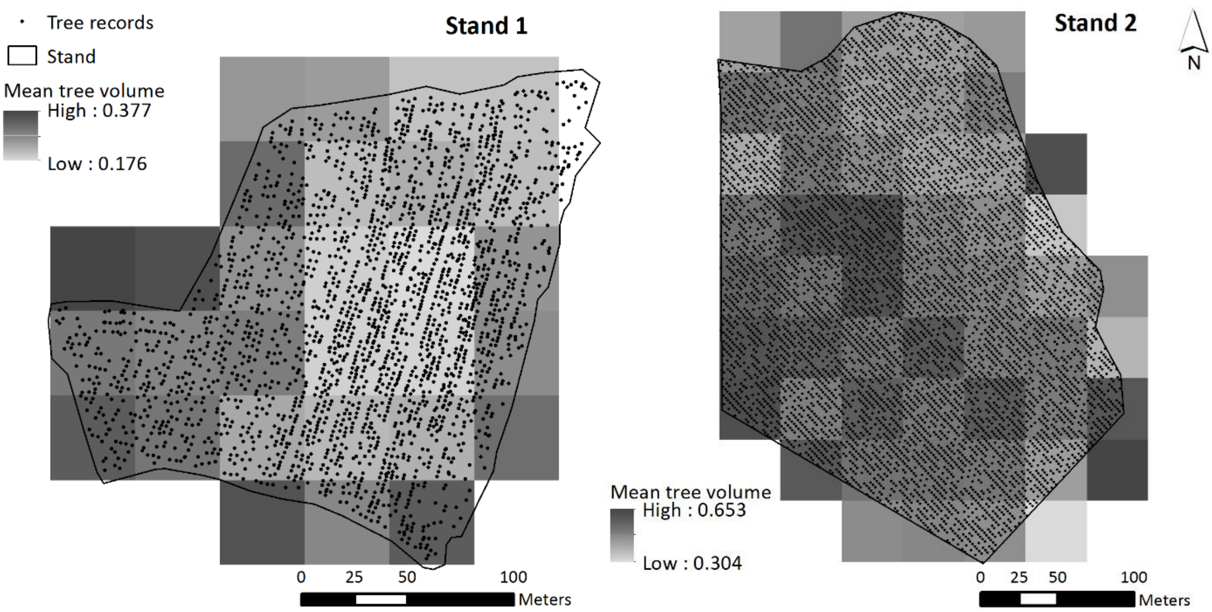

Figure 19: Stands 1 and 2 divided in 40m cells with value of mean tree volume (m^3) per cell used in grouping method A. Only cells with 30 or more trees records were used.

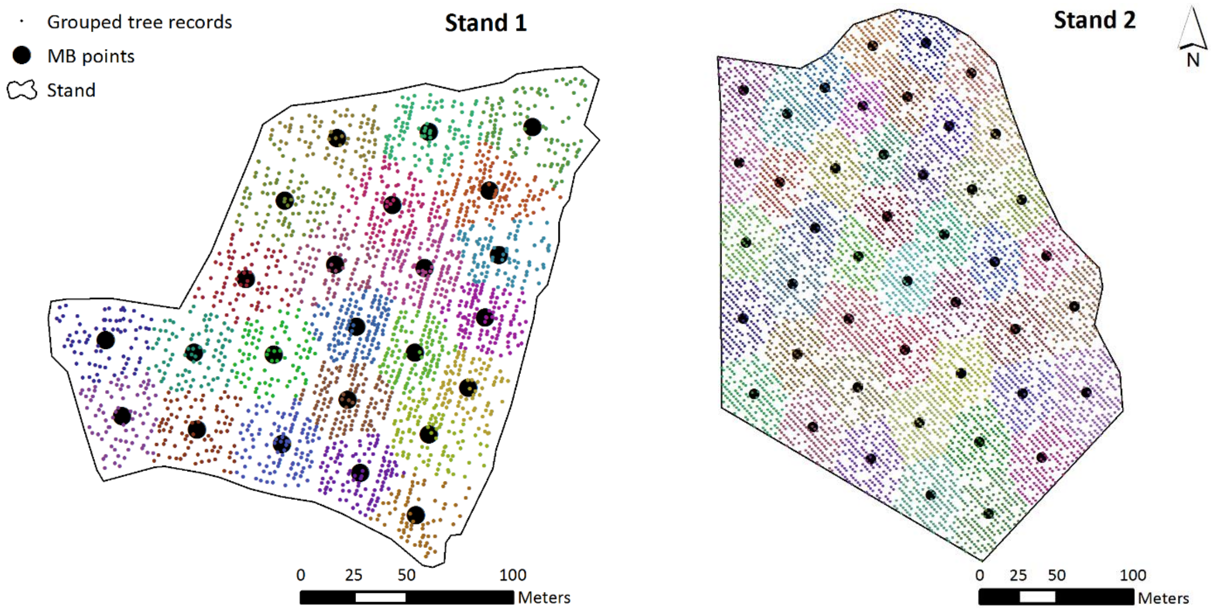

Figure 20: Detail of grouping method B. Stands 1 and 2 with tree records grouped (records with equal colour) based on their proximity, and mean centre points used for interpolation. MB: Grouping method B.

Creating stocking surfaces

Stocking for each stand was determined using three methods (methods 1, 2 and 3). Method 1: Using georeferenced square inventory plots of 18 x 18 m (resulting area of 324 m^2) with a sampling intensity of one plot per hectare. This sampling intensity was used because the pre-harvest inventory (PHI) data available from the harvester data stands used plots of 300 m^2, and the goal of this work is to develop a methodology to apply to harvester data. Then, for Stands 1 and 2 similar sampling size and distribution were used. To obtain a data layer, the stocking was interpolated from the inventory plots using the Geostatistical Analyst extension from ArcGIS. For each stand, several interpolation methods were explored and compared using the Cross Validation Comparison from ArcGIS. The interpolation method with the best statistics (i.e. value of the root-mean-squared prediction error closer to the value of average estimated prediction standard error, root-mean-square standardized is closer to one, and smaller root-mean-squared prediction error (Esri Inc., 2014b)) was chosen. The visual representation of the surface was also considered when statistic differences were small. Using inventory plots, it is possible to explore whether stocking is spatially dependent, i.e. if the variation in stocking across the stand presents a certain pattern across the area (Biondi et al., 1994; Mello et al., 2005; Mello et al., 2009). This information helps the selection of productivity mapping models because some of these models assume the stocking is homogeneous across the stand. One limitation of method 1 is it requires the availability of inventory data.

Method 2: Dividing the total number of trees by the area of the stand to generate average stocking. This method is recommended only in situations where stocking across the area is homogeneous as in Stand 2.

Method 3: Dividing the stand in square cells of 40 x 40 or 60 x 60 m for Stand 1 and Stand 2 respectively. Using the tool Point to Raster (Figure 21), the count of the number of trees in each cell was assigned to each cell. This value was normalised on a per hectare basis and a raster surface was interpolated using the Ordinary Kriging method. Only cells that were completely within the stand were considered. As was concluded in Chapter 3, the CV of the stocking across stands stabilizes at 40 to 60 m cell size, therefore, these cell sizes are used with the assumption that the effect of tree positional inaccuracy is negligible when applied to harvester data. The advantage of method 3 is that a productivity map can be generated purely from .stm or .pri files and it can be established if stocking is spatially dependent. The result of each stocking method is a raster surface representing stocking rate (per hectare) across the stand.

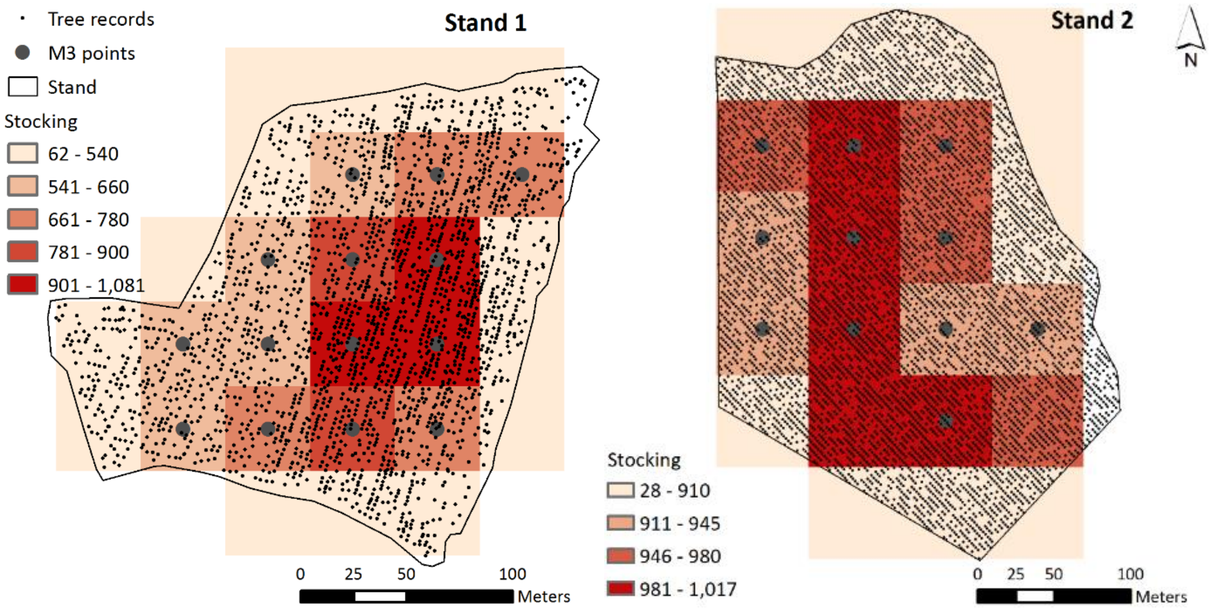

Figure 21: Stand 1 and 2 raster maps and cell centre point used to create the stocking (trees ha^{-1}) layer in method 3 (M3). Stand 1 divided in 40 m cells and Stand 2 in 60m cell.

Creating the model-generated productivity maps

Models 1 to 6 were built using the ModelBuilder tool in ArcGIS 10.2.2. Each model is the result of a factorial combination of the two methods of grouping trees (methods A and B) and the three methods of determining stocking (methods 1, 2 and 3) (Table 11). For models 1 to 3, a raster surface of volume per hectare (m^3 ha^{-1}) was derived by multiplying average tree size (m^3) by the stocking (trees ha^{-1}), whereas models 4 to 6 followed a similar process multiplying a point layer (m^3) by a raster layer (trees ha^{-1}) creating a point surface. Figure 18, Figure 22 and Figure 23 present the processes used in developing models 1 to 7 for preparing the yield maps. The output raster of models 1 to 3 were converted using the tool Raster to Point, which created a point layer with a single point at the centre of each cell with the value of productivity from each cell.

The point data layer from model 7 was obtained from conversion of the raster to a point layer assigning the values of productivity (m^3 ha^{-1}) from each cell to their centre points (Figure 18).

The values of the resulting point layer from each model were interpolated to create a productivity map (or yield map) of each stand. For the seven models, several options of interpolation methods were explored and Ordinary Kriging were finally selected as it is the most robust method (Griffin, 2010).

An additional productivity map from interpolated pre-harvest inventory (PHI) plots (Table 13) using Ordinary Kriging was created to include in the comparison. This map was included to establish whether the results of models based on a census of all trees are different from a productivity map generated from plot samples. As mentioned in the introduction, the hypothesis is that from a census the variations in short distances can be captured, whereas from plot samples the captured variations are on a major scale.

Table 13: Pre-harvest inventory (PHI) plots and range of stocking and productivity values for all stands.

		Range of stocking (trees ha^{-1})		Range of productivity (m^3 ha^{-1})	
	PHI plots	**Min**	**Max**	**Min**	**Max**
Stand 1	3	586	1265	147.4	193.8
Stand 2	6	833	1142	431.4	547.4
Stand 3	6	900	1133	385.5	579.7
Stand 4	9	633	1033	154.9	267.6
Stand 5	6 [a]	1033	1333	nd	nd
Stand 6	4	667	900	238.7	342.6
Stand 7	7	600	1000	213.4	357.7

[a] Plots for this stand were not georeferenced; nd= No data available

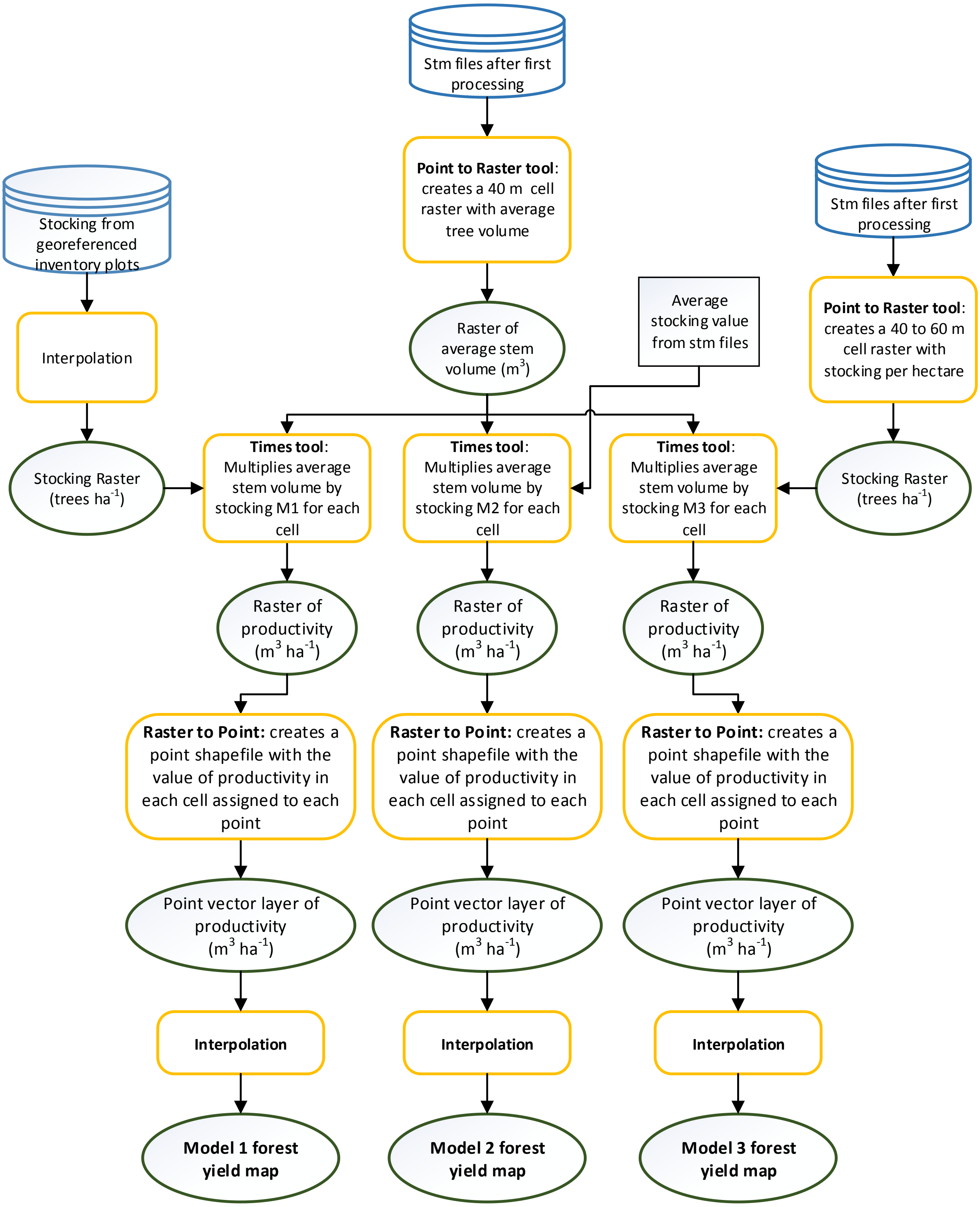

Figure 22: Diagram of models 1 to 3 processes, showing the sequence of steps. Blue boxes represent databases, yellow boxes represent the ArcGIS tool used, and green boxes represent layer data outputs. M1: Stocking method 1, M2: Stocking method 2, M3: Stocking method 3.

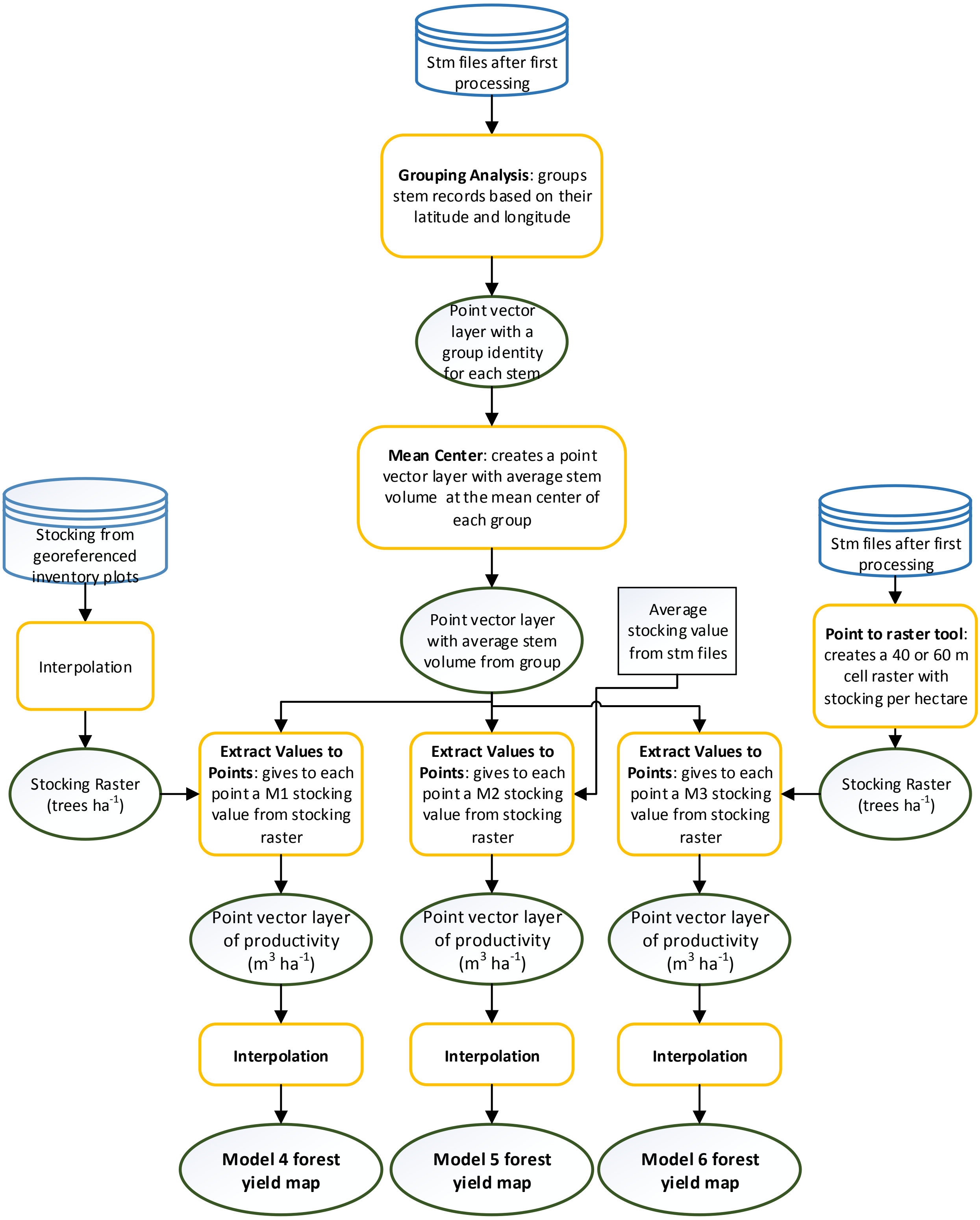

Figure 23: Diagram of models 4 to 6 processes, showing the sequence of steps. Blue boxes represent databases, yellow boxes represent the ArcGIS tool used, and green boxes represent layer data outputs. M1: Stocking method 1, M2: Stocking method 2, M3: Stocking method 3.

Accuracy assessment

To assess the accuracy of each productivity model, approximately 100 points randomly distributed over the stand were generated for each stand (Figure 24); the tool Generate Random Points from ArcGIS was used for this process. Only the points that fell inside the usable area of 40 m cells were used for the comparison. The usable cells are those whose area is completely inside the stand boundaries; 13 and 32 were the number of usable cells for Stand 1 and 2 respectively. The distribution of the random points were checked to assure that all cells were covered. For the assessment, a process model was created in ArcGIS; from the productivity model surfaces (in raster format) the value from each productivity model at each point were extracted using the tool Extract Multi Values to Points. The result was a point vector layer with the value from each productivity model (8 in total) and the reference map at each one of the random points. The resulting layers were exported as a table and analysed in an Excel spreadsheet.

An analytical technique was used to assess the accuracy of each model-generated productivity map by comparing the estimates with the reference productivity values (Congalton, 1991). The technique consisted of subtracting each model value from the reference value and counting the proportion of values that were within ± 5 %, ± 10% and ± 20% of the reference value. A matrix with the results was created with the percentage of points registered in each error class.

To aid the ranking of models for each stand, a criterion was built weighting the percentage of points counted in each class; higher accuracy had higher weighting factor. The proportion of points within ± 5% was multiplied by a factor of 0.5, within ± 10% by a factor of 0.3 and within ± 20% by a factor of 0.2. This score is called the performance score; the higher the performance score the better the model.

Selected models application to harvester data

Finally, three models were chosen and applied to five harvester data stands (Stands 3 to 7; Table 8). The selection of models was based on the performance score, and it also considered the versatility to apply the model to stands with and without variability in stocking and characteristics of the stand, such as area and shape. The cell size used for each stand, model and the three variables (productivity, stocking and mean tree volume) were as per the results and discussion in Chapter 3 (Figure 12 to Figure 17).

To assess the similarity of the three selected models plus the PHI model, the same analytical technique used in the accuracy assessment was applied, in this case the score is called the similarity score. The model with the highest performance score in the accuracy assessment was used as a reference to compare the result in all stands. Stands 1 and 2 were also included in this analysis to compare the results from harvester data and stands with accurate tree location.

RESULTS

Models

Reference maps

The reference maps for Stand 1 and 2 are presented in Figure 24. Values of productivity of Stand 1 ranged from 133 to 194 m^3 ha^{-1} presenting a pattern of higher productivity at the centre of the stand, which decreases towards the North and West edges. The productivity within the used area was divided into four classes for visual comparison with the model-generated productivity maps. Stand 2 productivity varied between 421 to 640 m^3 ha^{-1} showing lower productivity in the north and northeast part of the stand and higher at the centre, south and west. For this stand, five classes of productivity were used in the division due to the range of values is larger than Stand 1.

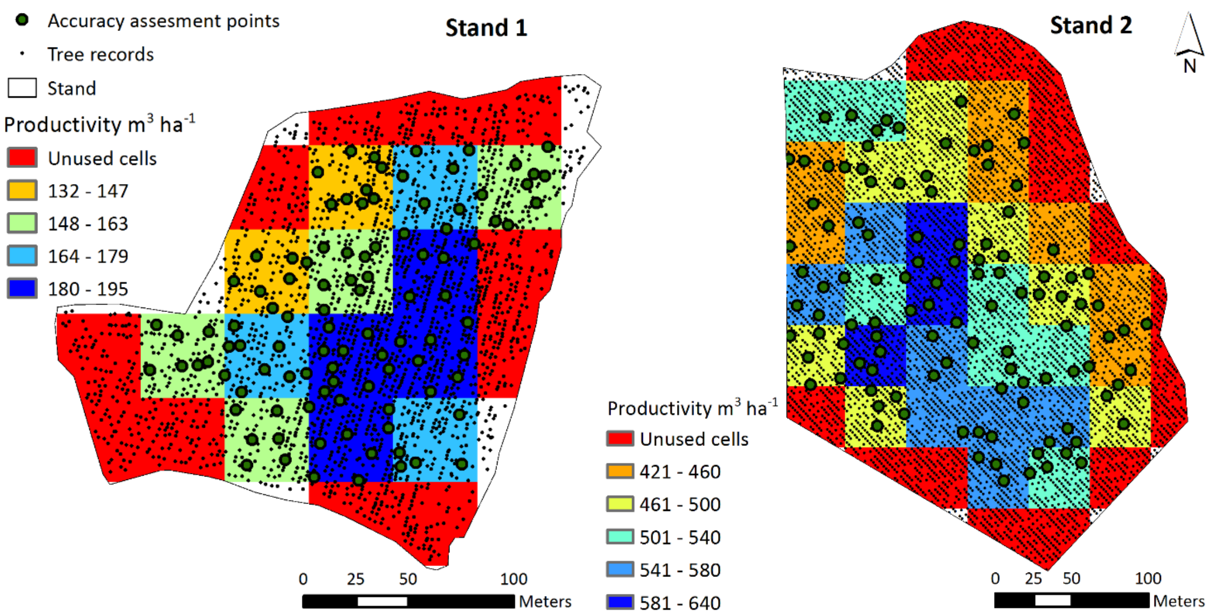

Figure 24: Stand 1 and 2 40 m cell reference maps with points for accuracy assessment. Cell values represent reference productivity values (m^3 ha^{-1}). Only cells that have the total area inside the stand have points for accuracy assessment, all other cells (in red colour) are excluded as reference because part of their area is outside the stand boundaries.

Mean tree volume and stocking

The layers of mean stem volume values using tree grouping methods A (raster layer) and B (point layer) are shown in Figure 19 and Figure 20 respectively. Table 12 summarizes the number of cells and groups, and average number of trees per cell and per group for each stand, the quantities from both methods are similar for each stand.

Stocking from method 2 is the average value of stocking for each stand (Table 8). The output of the stocking layers obtained from methods 1 and 3 presented slightly different surfaces for both stands. Method 1; for Stand 1 the interpolation method that presented better statistics (root-mean-square of prediction errors) and visual representation was Radial Basis Function (RBF), which is a type of spline (Esri Inc., 2014b). RBF also predicts values above and below the maximum and minimum of the interpolated points, which is desirable when the number of points is low (3 in this case). The map resulted in a surface of stocking ranging from 369 to 1100 trees ha^{-1} (Figure 25 and Table 13). Similarly, the result of the interpolation using method 3 and a 40m cell size was a gradual surface with values ranging from 491 to 1171 trees ha^{-1}. The results from both methods reflect the variation in stocking across the stand.

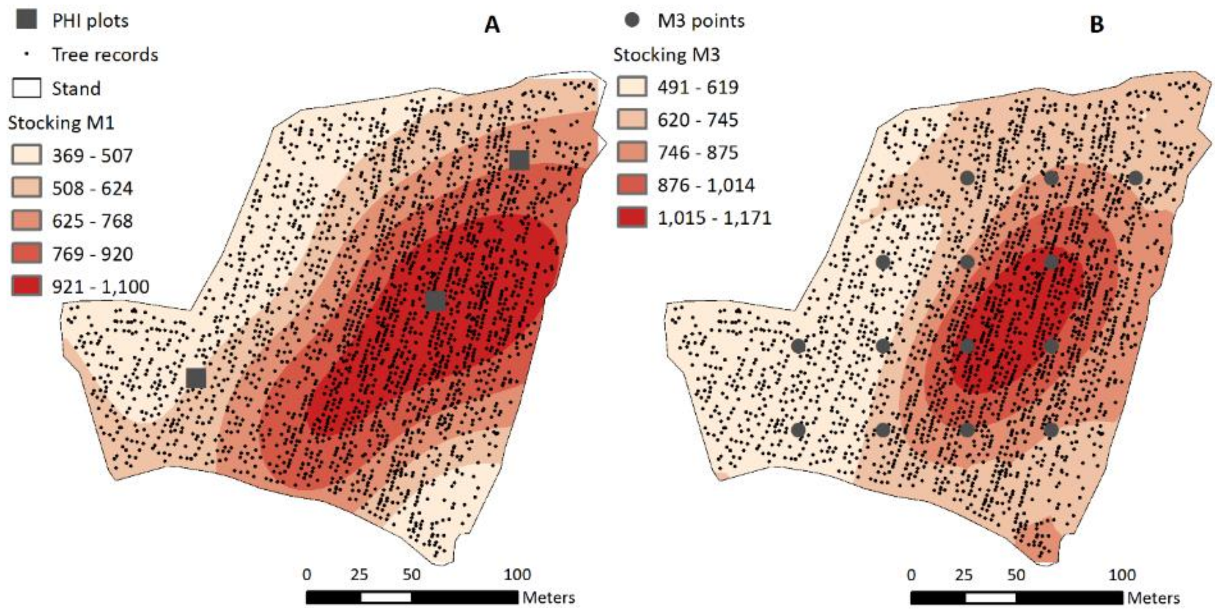

Figure 25: Stand 1 interpolated maps of stocking using method 1 (A) and method 3 (B). Location of the 3 plots and 14 points used for interpolation. PHI: location of pre-harvest inventory plots; M1: method 1; M3: method 3.

For stand 2, Ordinary Kriging was the geostatistical method with better statistics (value of the root-mean-squared prediction error closer to the value of average estimated prediction standard error). The stocking layer applying method 1 presented small variations ranging between 989 to 1008 trees ha^{-1} (Figure 26 and Table 12). The result of the interpolation from method 3 showed an even smaller variation ranging from 957 to 973 trees ha^{-1} (Figure 26), this range of values were around the overall average of 967. Both results reflect that the stand has even stocking distribution; however, the range of values from method 1 were higher than the stand average.

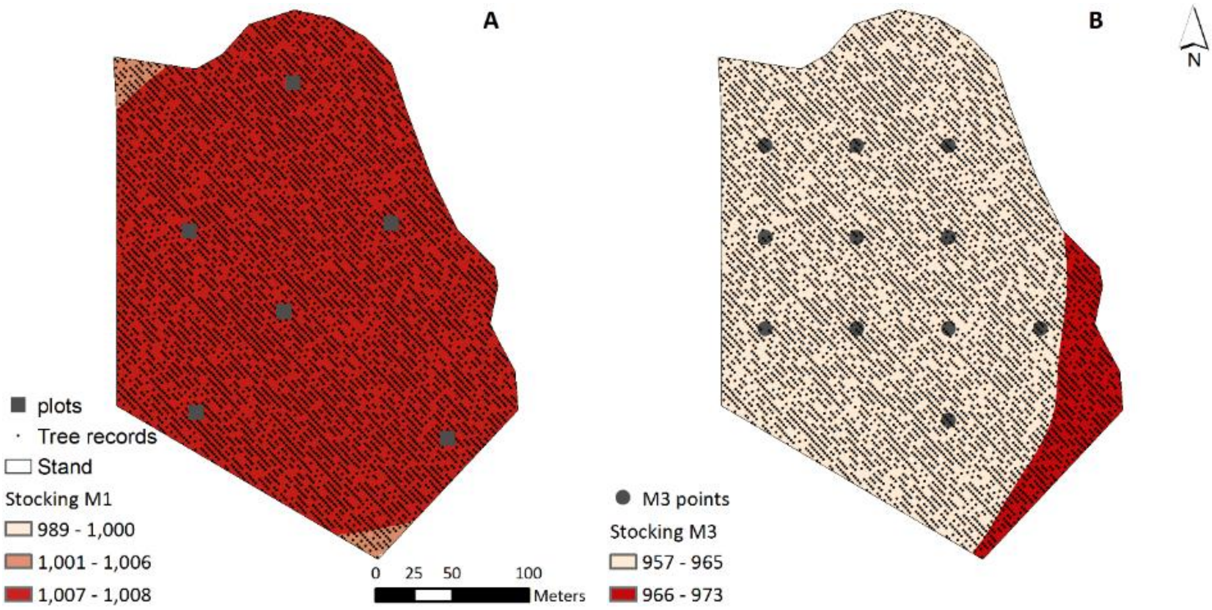

Figure 26: Stand 2 interpolated maps of stocking using method 1 (A) and method 3 (B). Location of the 6 plots and 11 points used for interpolation. PHI: location of pre-harvest inventory plots; M1: method 1; M3: method 3.

Productivity maps

Productivity maps obtained from models 1 to 7 for Stand 1 presented surfaces with different pattern in productivity. The similarities between maps and extreme values were related to the use of similar methods for determining stocking (Figure 27). Model 1 surface was similar with model 4 as was model 2 with model 5, and model 3 with model 6. Models 1 and 4 presented the highest difference between maximum and minimum productivity values (135 and 146 m^3 ha^{-1} respectively) and a gradient of productivity similar to the reference map, with higher values at the low centre and east centre part and lower towards the northwest and southeast corner of Stand 1. Models 2 and 5 indicated an intermediate difference between extreme values and a productivity pattern opposed to the other models, with lower productivity along the centre of the stand with north south direction and higher productivity at the west side and southeast corner of the stand. A smaller difference between extreme values resulted from models 3 and 6 with values that approximately halved the values resulted from models 1 and 4. The productivity pattern for these two models indicated higher productivity at the southeast and east sector decreasing towards west, northwest and the lowest values at north. Zones of higher and lower productivity from these two models are coincident with the reference map. Whilst the smallest range between extreme values (42 m^3 ha^{-1}) were from model 7, which presented higher productivity at the centre and southeast part of the stand decreasing towards north and west. The productivity zones are coincident with the reference map. PHI model output resulted in a homogeneous productivity surface (170 m^3 ha^{-1}).

Stand 2 productivity maps from models 1 to 7 had coincident productivity zones, which increase in the direction Northeast to Southwest (Figure 28). The amplitude of values are also similar, minimum of 158 m^3 ha^{-1} for model 7 and maximum of 183 m^3 ha^{-1} for model 1. Extreme productivity values showed slightly higher differences with minimum values ranging from 416 to 437 m^3 ha^{-1} and maximum between 573 and 618 m^3 ha^{-1}. The productivity map obtained from inventory plots presented a considerably narrower range of values from 460 to 534 m^3 ha^{-1} and a productivity gradient increasing in the direction east to west.

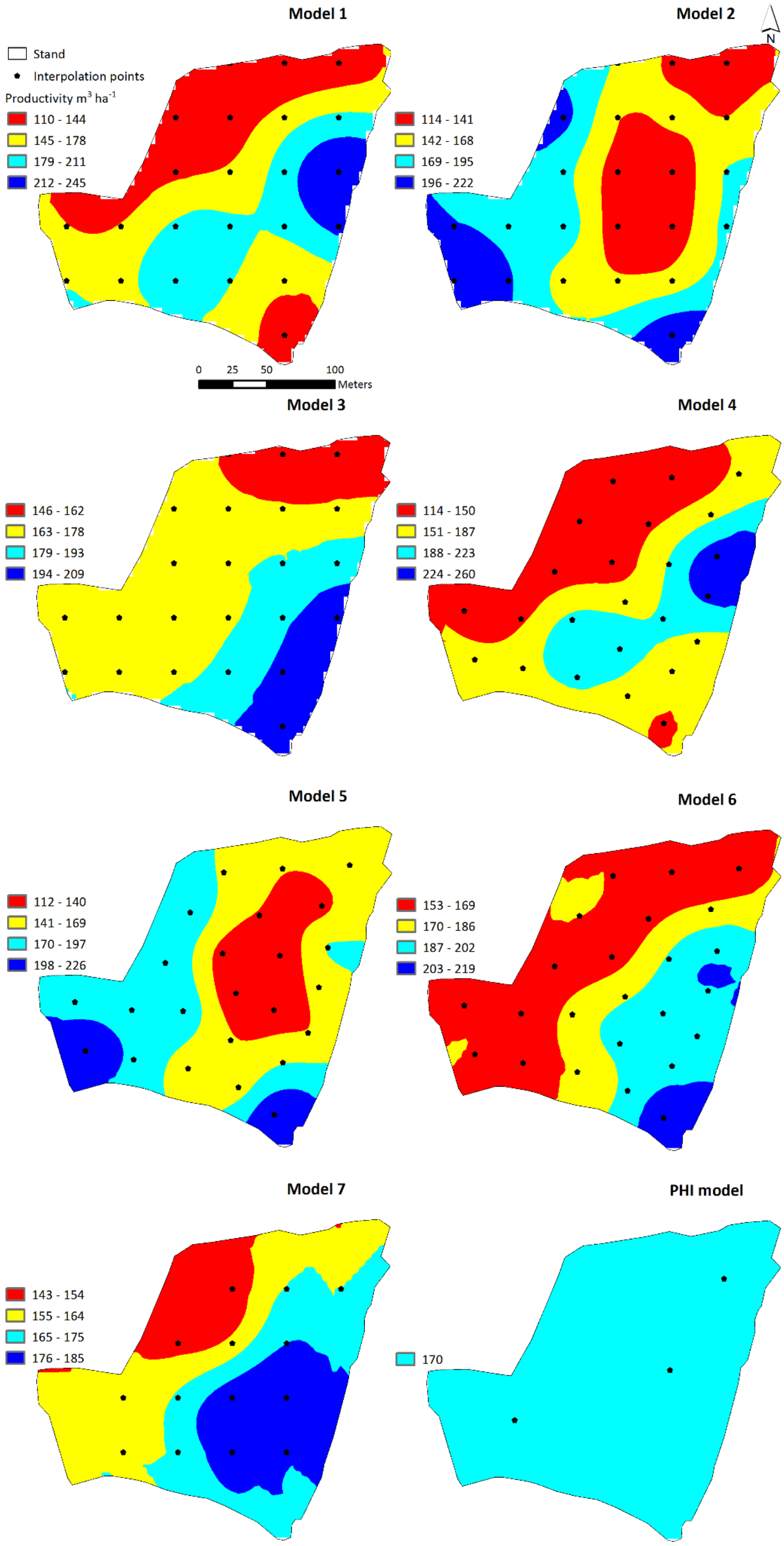

Figure 27: Productivity maps generated from models 1 to 7 and PHI model for Stand 1. Detail of interpolation points for each model. Range of values are in m^3 ha^{-1}.

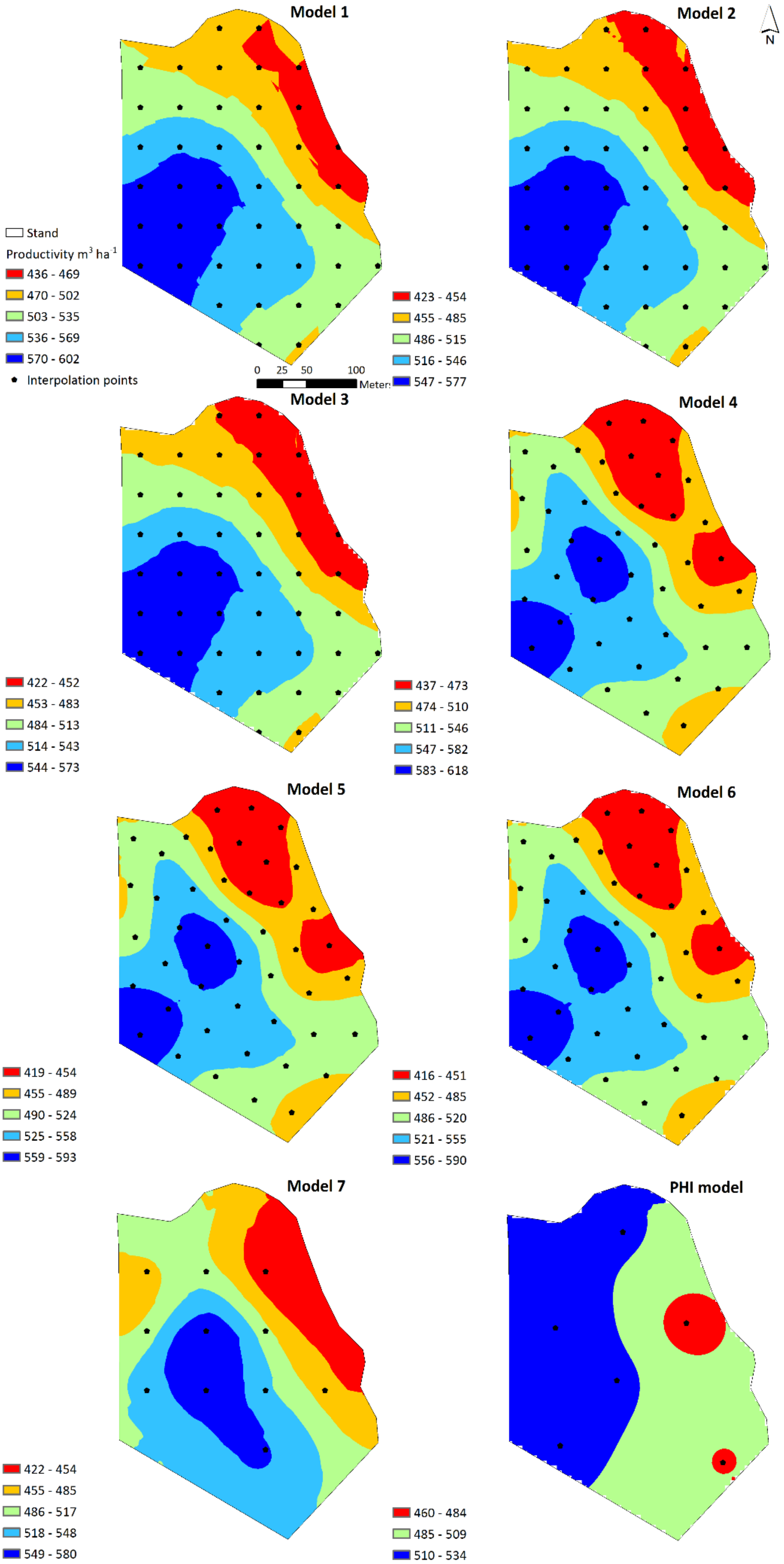

Figure 28: Productivity maps generated form models 1 to 7 and PHI model for Stand 2. Detail of interpolation point for each model. Range of values are in m^3 ha^{-1}. PHI model map presents only three classes of productivity as the amplitude of values is lower than all other models.

Accuracy assessment

A total of 101 and 111 points for Stand 1 and 2 respectively were used to evaluate the accuracy of the 8 models (Figure 24). Accuracy varied between models and accuracy target (Table 14); for 5% accuracy, results ranged from 13 to 54% for Stand 1 and from 42 to 52% for Stand 2. When the allowed accuracy was 20%, percentages varied between 56 and 100%, and between 92 and 100% for Stands 1 and 2 respectively. Model 7 was the most accurate for Stand 1 (performance score of 74), followed by models 6 (63), models 3, 1 and 4 (55-54); the PHI model scored relatively low (performance score of 48); while models 2 and 5 were the least accurate (30 and 25 respectively) and also presented an inverted productivity pattern across the stand. As for Stand 1, model 7 scored the highest for Stand 2 (performance score of 72); models 2, 3, 5, 6, 4 and the PHI model performed similarly well (66 to 62), while model 1 was the least accurate (60). The differences in performance scores between models for Stand 2 were considerably smaller than for Stand 1.

Table 14: Accuracy assessment matrix of models 1 to 7 and PHI compared with references maps from Stands 1 and 2. Includes total number of points used in the assessment and performance (weighted) scores for final evaluation; higher performance score more accurate model.

		Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**PHI**
Stand 1		Number of points	101	101	101	101	101	101	101	101
	% of points	within ±5%	35	16	38	37	13	50	54	21
		within ±10%	65	30	60	60	24	68	90	65
		within ±20%	91	65	91	88	56	91	100	91
		Performance score	**55**	**30**	**55**	**54**	**25**	**<u>63</u>**	**<u>74</u>**	**48**
Stand 2		Number of points	111	111	111	111	111	111	111	111
	% of points	within ±5%	43	48	45	46	43	42	52	45
		within ±10%	68	74	76	68	76	75	86	68
		within ±20%	93	100	100	92	98	98	100	94
		Performance score	**60**	**66**	**65**	**62**	**64**	**63**	**<u>72</u>**	**62**

Selected models application to harvester data

Models 7, 6 and 3 were chosen to be applied to the five harvester data stands; as model 7 was the best model for Stands 1 and 2, it was used as a reference for the similarity assessment. Model 6 was the second best for Stand 1 and similar to models 2, 3 and 5 for Stand 2. While model 3, scored below model 6 for Stand 1 and similar to 6 for Stand 2. Models 2 and 5 scored relatively high for Stand 2, but very low for Stand 1, and presented an inverted productivity pattern compared with the reference map, which, indicates that their application is not appropriate to stands that have variation in stocking across the area (Table 14). Exploring the variability of stocking from inventory data for all harvester stands, all stands presented some variability (Table 13), therefore, the use of models 2 or 5 was not adequate.

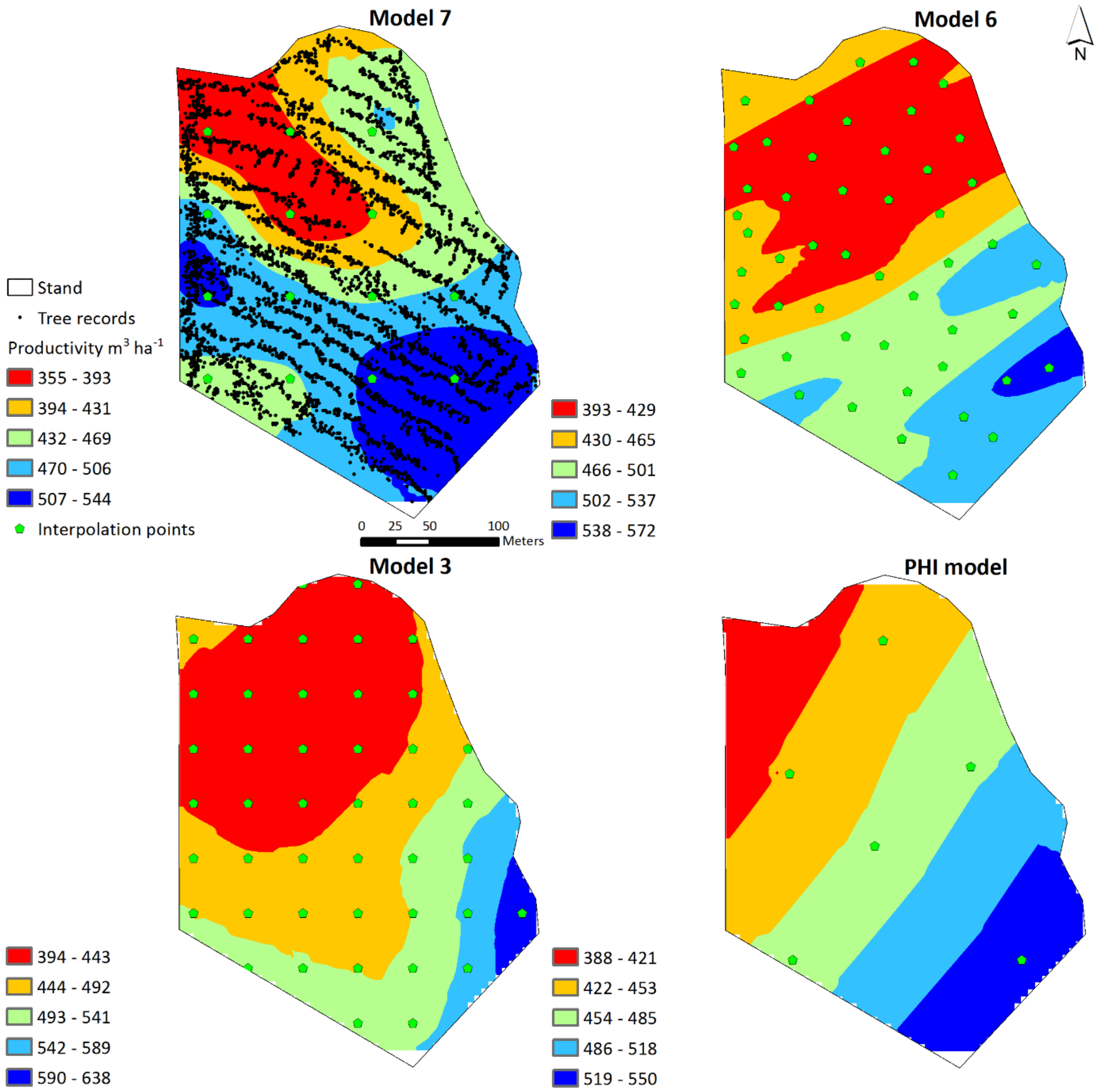

Figure 29: Stand 3 productivity maps and interpolation points applying selected models (model 7, 6, 3 and PHI). Model 7 map also shows pattern of tree records aligned on harvester path from harvester data. Values of productivity are in m^3 ha^{-1}.

Productivity maps from the five harvester data stands using the three selected models and from inventory plots are presented in Figure 29 to Figure 33. For Stands 3, 4, 5 and 7 (larger areas), the maps are similar, as they presented coincident location of the areas with higher and lower productivity. In addition, the scores of the comparison with model 7 (similarity scores) are relatively high ranging from

54 to 68 and similar for model 6 and model 3 for each stand (Table 15). The pattern of variation however, presented some differences in the shape and transition of the areas. When stands are smaller, such as Stand 6 for example, the reduced number of points for model 7 made the similarity (given its low similarity score) with models 6 and 3 lower. Consequently, the location of high and low productivity zones are different. For all stands, the maps from model 6 and 3 are very similar as was observed for Stands 1 and 2 (Table 15).

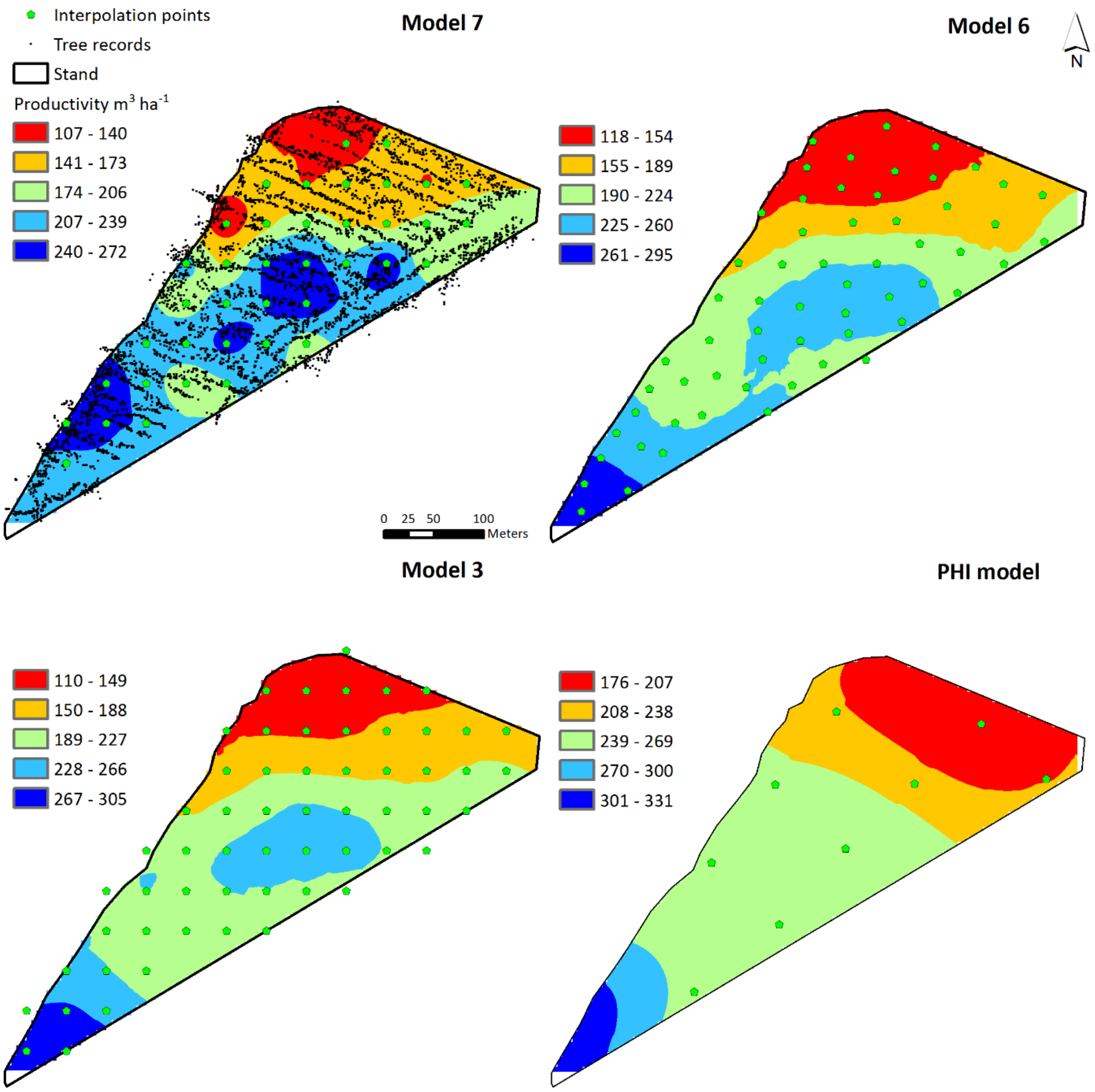

Figure 30: Stand 4 productivity maps and interpolation points applying selected models (model 7, 6, 3 and PHI). Model 7 map also shows pattern of tree records aligned on harvester path from harvester data. Values of productivity are in m^3 ha^{-1}.

The maps from PHI models, alternatively, presented a low similarity score for Stands 4, 6 and 7. Whereas, for Stand 3 the zones, range of productivity and similarity scores were similar.

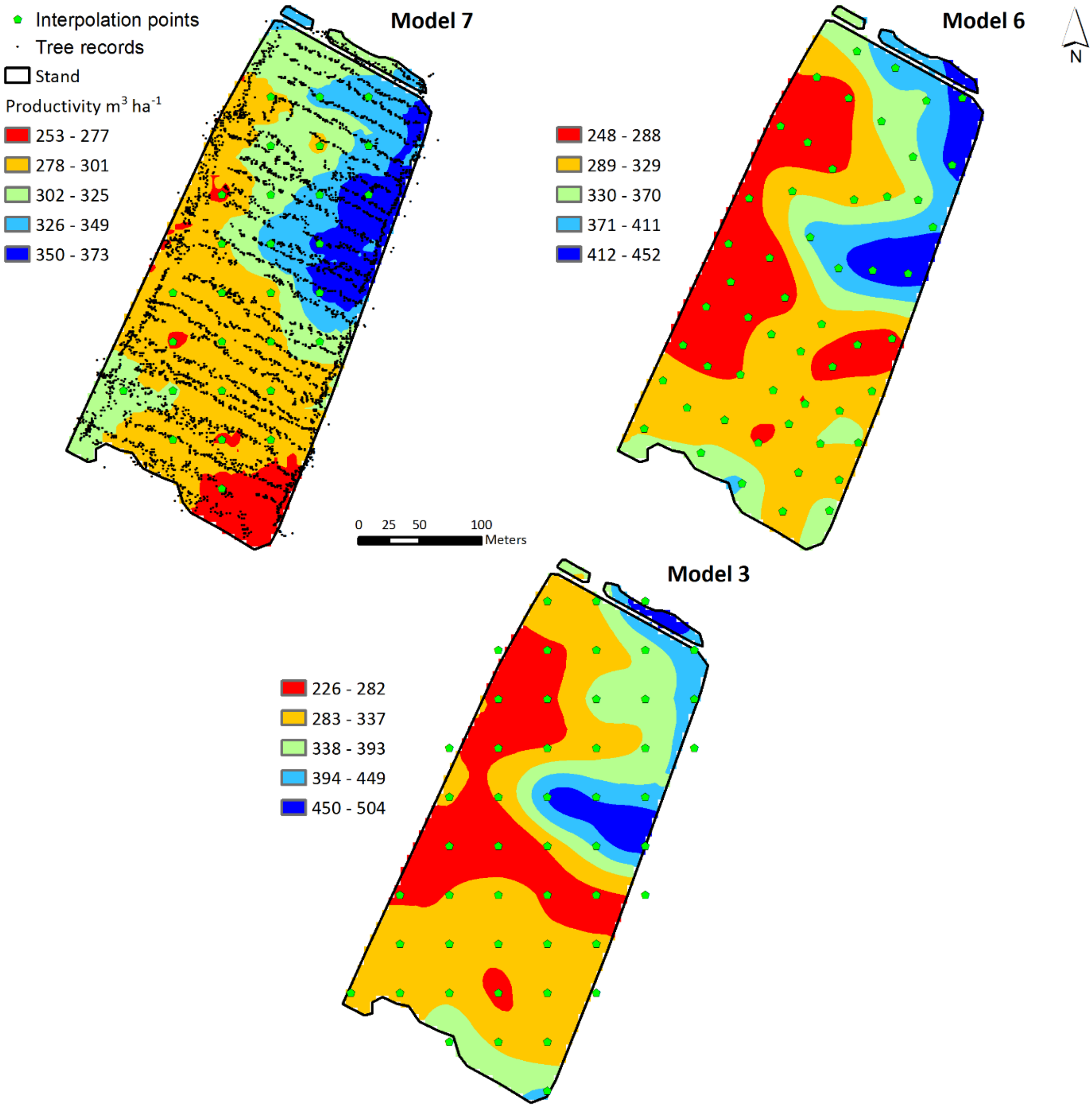

Figure 31: Stand 5 productivity maps and interpolation points applying selected models (model 7, 6 and 3). Model 7 map also shows pattern of tree records aligned on harvester path from harvester data. Values of productivity are in m^3 ha^{-1}.

Table 15: Similarity assessment matrix for all stands comparing models 6, 3 and PHI against model 7; and a comparison between models 3 and 6. Includes total number of points used in the assessment and similarity scores; higher score more similar the compared models.

		Model comparison	6 vs 7	3 vs 7	PHI vs 7	3 vs 6
Stand 1		Number of points	101	101	101	101
	% of points	within ±5%	56	52	44	81
		within ±10%	87	85	83	100
		within ±20%	100	100	100	100
		Similarity score	**74**	**72**	**67**	**91**
Stand 2		Number of points	111	111	111	111
	% of points	within ±5%	75	83	45	87
		within ±10%	98	100	90	99
		within ±20%	100	100	100	100
		Similarity score	**87**	**91**	**70**	**93**
Stand 3		Number of points	120	120	120	120
	% of points	within ±5%	46	37	54	78
		within ±10%	75	78	78	96
		within ±20%	98	98	99	100
		Similarity score	**65**	**61**	**70**	**88**
Stand 4		Number of points	119	119	119	119
	% of points	within ±5%	45	50	14	50
		within ±10%	75	79	29	87
		within ±20%	96	96	56	97
		Similarity score	**64**	**68**	**27**	**71**
Stand 5		Number of points	122	122	*	122
	% of points	within ±5%	35	37	*	62
		within ±10%	61	65	*	90
		within ±20%	91	87	*	100
		Similarity score	**54**	**55**	*****	**78**
Stand 6		Number of points	105	105	105	105
	% of points	within ±5%	20	20	18	79
		within ±10%	44	43	38	97
		within ±20%	73	80	71	100
		Similarity score	**38**	**39**	**35**	**89**
Stand 7		Number of points	151	151	151	151
	% of points	within ±5%	36	38	0	82
		within ±10%	74	74	5	97
		within ±20%	98	97	45	100
		Similarity score	**60**	**60**	**10**	**90**

* There was no georeferenced pre-harvest inventory (PHI) data available for stand 5

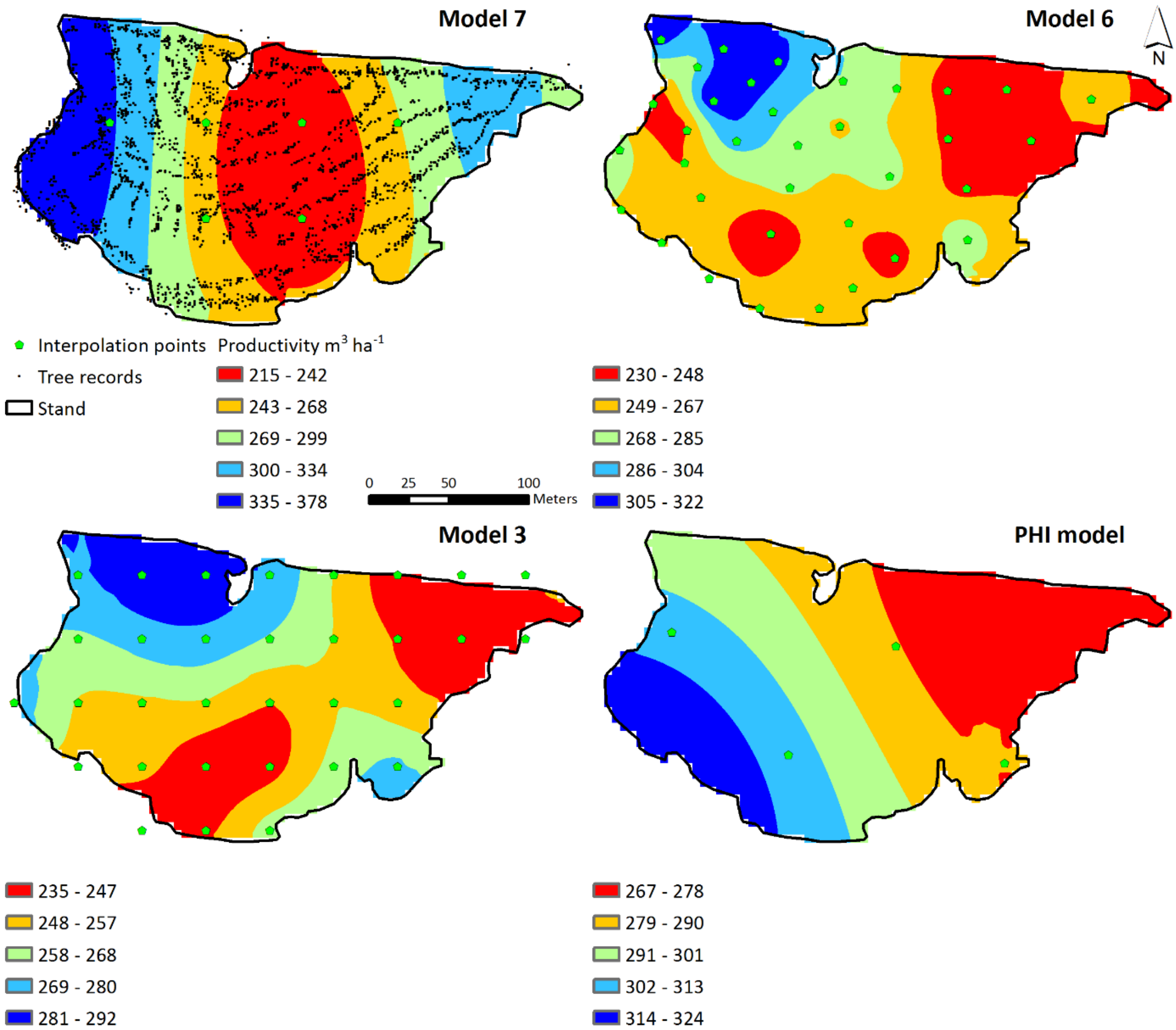

Figure 32: Stand 6 productivity maps and interpolation points applying selected models (model 7, 6 3 and PHI). Model 7 map also shows pattern of tree records aligned on harvester path from harvester data. Values of productivity are in m^3 ha^{-1}

DISCUSSION

Accurate data stands – Stands 1 and 2

As an interpolation from points derived directly from the reference map, the higher accuracy of model 7 for both stands was expected (Table 14). Differences in accuracy and productivity patterns between models 1 to 6 varied between both stands. The variability of stocking was a determining factor. The homogeneous stocking distribution in Stand 2 explains the similarities between maps and performance scores from models 1 to 6 and the similar performance score of the PHI model (Table 14 and Figure 28). Thus, the use of different methods to calculate stocking resulted in similar values, and therefore the productivity maps are similar. The PHI model resulted in the most dissimilar productivity map and had considerably narrower extreme values for Stand 2 as is interpolated from a lower number of points (6) (Figure 28).

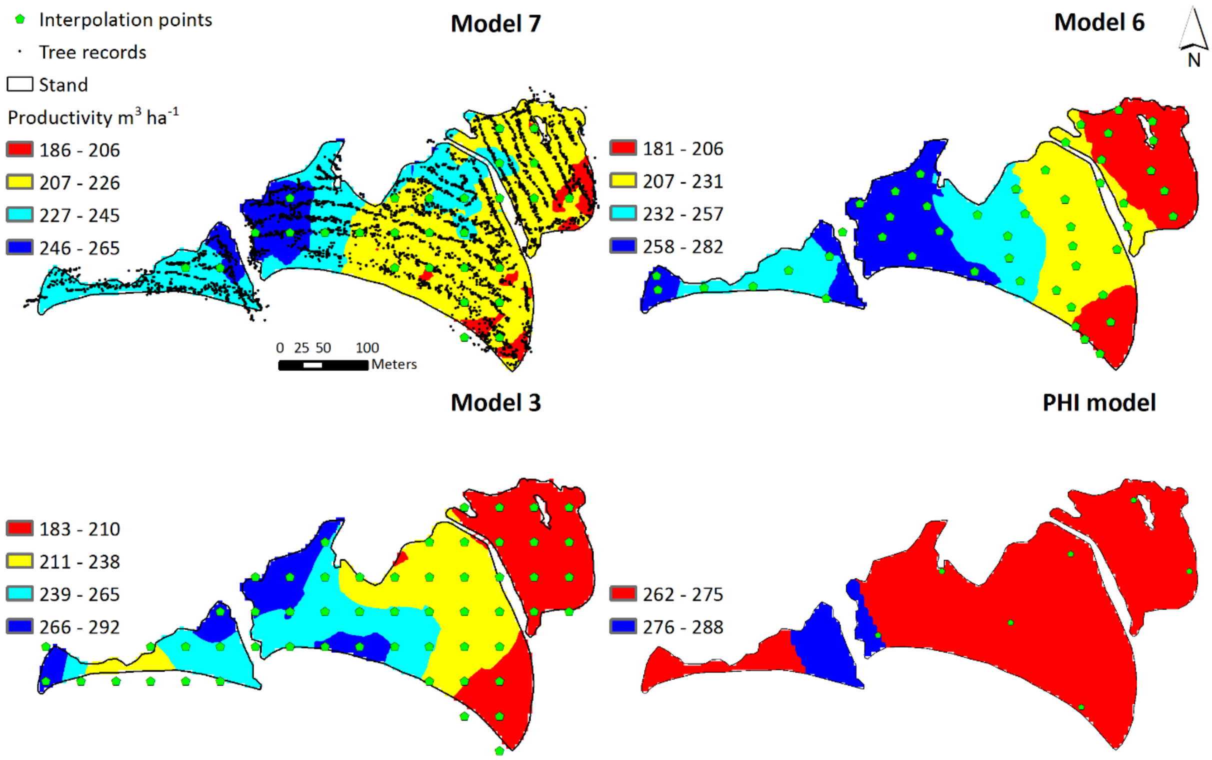

Figure 33: Stand 7 productivity maps and interpolation points applying selected models (model 7, 6 3 and PHI). Model 7 map also shows pattern of tree records aligned on harvester path from harvester data. Values of productivity are in m3 ha-1

The low accuracy of models 2 and 5 (performance scores of 30 and 25 respectively) and the inverted productivity pattern shown in the generated map for Stand 1 is because the assumption of homogeneous stocking used in the models induced a high level of error, as there were differences in stocking across the stand (Table 14, Figure 27). Conversely, this factor caused the higher accuracy of these two models for Stand 2 (performance scores of 66 and 64).

Models 1 and 4 for Stand 1 scored higher in their performance (55 and 54 respectively) than the PHI model (48) and had similar maps to the reference map. Whereas, the PHI model output a homogeneous surface without variation in productivity (Figure 27), indicating that with the used sampling intensity the differences in productivity cannot be modelled for this stand. This suggests the use of inventory plots to determine stocking combined with mean tree volume from harvester data is a better option than interpolating productivity values directly from inventory plots. One disadvantage of these models is it requires the availability of inventory data. Model 6 was the second best model for Stand 1 and similar to other models for Stand 2, therefore a good representation of variations in productivity from this model is expected, especially for areas that have variations in stocking. While for model 3, performance score was lower than model 6 for Stand 1, therefore the grouping method B (Table 11) would be a better option than method A for stands with heterogeneous stocking.

Selected models application to harvester data

Model 7 was the best option to apply to harvester data using a cell size where the coefficient of variation for the volume per hectare is stable (Figure 12, Figure 13 and Figure 24); for the studied stands this was 40 to 60 m. Nevertheless, comparing the similarity scores from harvester data with Stands 1 and 2, the values are lower – 55 to 68 vs 72 to 91– (Table 15), which suggests that there are still an effect of the inaccuracy of harvester records (described in detail in Chapter 3). This effect, compromises the applicability of this model for harvester data stands smaller than 5 ha, for example Stand 6. For this stand, the similarity scores, when compared with models 3 and 6, are considerably lower (39 and 38 respectively) than for the other stands (54 to 68). Consequently, the location of high and low productivity zones are different. This occurred because the number of 60 m cells that lie completely within the stand boundaries represent only 50% of the stand (Table 9), leaving the other 50% of the area out of the assessment. In such situations, a model that assesses stocking and mean tree volume separately, such as models 6 and 3, would be a better option.

As model 6 is the second best model for Stand 1 and similar to other models for Stand 2, it is recommended for areas where model 7 is a questionable option (e.g. Stand 6). This model also showed high scores of similarity with model 7 (the reference) for all harvester data stands, except the smallest stand, Stand 6 (Table 15). Otherwise, models 3 may be used with lower expected accuracy, however higher than the option of using inventory plots (Table 14 and Table 15).

The differences in the map patterns and range of similarity scores (with model 7) from PHI productivity maps were inconsistent among the stands (Table 15, Figure 29 – Figure 33) and congruent with the results from Stands 1 and 2 (Table 14, Figure 27 and Figure 28). These inconsistencies suggest a random behaviour, indicating that productivity maps from inventory plots with an intensity of one plot per hectare assessing 3% of the area are less accurate at representing the variations in productivity at sub-stand scale.

General comments

All proposed models for mapping stand productivity have their pros and cons; while, some of them performed better, all of them are applicable to map productivity at a sub-stand scale with better-expected results than the use of inventory plots with the sampling intensity used in this study. Models 7 and 6 are the best options because both models can generate productivity maps purely from harvester data. In addition, for areas with variation in stocking or where the variation is unknown, models 1, 3 and

4 can be used with lower expected accuracy. For areas that do not have variations in stocking, models 2 to 6 can be applied with similar expected accuracy as resulted for Stand 2 (Table 14). If models 2 or 5 are preferred –as they are simpler– the recommendation is to use the average stocking from stm files rather than the average from inventory plots, because the former is the result of a census of all trees, whereas, the latter comes from a reduced number of samples. Therefore, the representativeness of the area is better reflected from a census.

Larger areas are better to map as they fit a larger number of points for interpolation, resulting in better statistics. This is clear when comparing the maps generated from different models for larger stands (2, 3, 4 and 5), as the maps are similar (coincidental location of the areas with higher and lower productivity as well as the pattern of variation) with reference maps. As areas becomes smaller, the lower number of points makes the models weaker so their accuracy is lower and the pattern of variation is different between models (Stands 1 and 6). As such, one limitation of this project is the use of relatively small areas. Larger areas such as contiguous stands (of same species, ages and progeny) would result in more accurate maps as there are more points for interpolation, therefore reducing the edge effect. Furthermore, for small areas the creation of productivity maps remains a challenge because of the reduced number of points available for interpolation, which excludes a relatively large proportion of the area due to the edge effect (cells that are not fully in the stand). Based on the results of this study, a stand size limit of 4 to 5 hectares is estimated, when using a resolution of 40 to 60 m cell size.

The resulting cell size for grouping trees (or its equivalent number of trees) is larger than the average expected inaccuracy of tree location from harvester data (3 to 9 m with standard deviations up to 12 m) (Chapter 3). Hence, the grouping of trees counteracts both inaccuracy effects (GNSS location and head distance from the cabin) since the interpolation uses a value in an average location for a group of trees instead of each single value.

The next generation of harvesters would collect more accurate tree location data as the position of the head with respect to the machine base would be accurately estimated (Lindroos et al., 2015). In addition, the new version of StanForD, StanForD2010, can record data from not only the position of the machine, but also the position of the head, the angle of the crane and the bearing direction of the machine. Such advances may improve the quality and accuracy of productivity maps. However, using the models developed in this work for mapping total productivity, the spatial resolution would still be between 30 to 60 m as explored in Chapter 3 using Stand 1 and 2 data. If instead the focus is on mapping different assortments, timber quality or timber value maps (Taylor et al., 2006), the gain in accuracy might be beneficial.

For harvester data, the commercial recovered volume is the only data available. This is a limitation of using GNSS enabled stm files for mapping productivity. Hence, the total volume of the forest is underestimated. On the other hand, this is an advantage as companies may be interested in commercial merchantable timber instead of total wood volume.

Further study should overlay the productivity maps with digital layers of data (soil maps, topographic maps, and slope classes and aspect) to identify and quantify the factors driving the differences in productivity.

CONCLUSIONS

Productivity maps from harvester data (stm or pri files) can be created to assess the variability of productivity at sub-stand level. This requires the following steps: first, a cell size analysis for the variables of productivity, stocking and mean volume must be carried out to define an adequate cell size for interpolation. Then using the cell size at which the coefficient of variation of these variables stabilizes, one of the models (I recommend 7, 6 or 3) shall be selected to create the map.

Model 7, which is the interpolation of the productivity value assigned to the centre point of each usable cell, is the recommended model to apply to harvester data stands. However for areas smaller than 5 ha, when the adequate cell size is 60 m, a relatively high proportion of the area is excluded from the interpolation, thus, this model has limitations (Stand 6 for example). In this case better options are: model 6, which multiplies stocking from stm files records by the mean tree volume from grouping trees using their X and Y coordinates; or model 3, which also multiplies stocking from stm files records by the mean tree volume from grouping trees dividing the stand into cells.

Productivity maps from GNSS enabled harvester data made it possible to map at sub stand level the variations in productivity stocking and mean tree volume; whereas productivity maps from inventory plots with an intensity of one 300 m^2 plot per hectare showed inconsistent results.

An idealised future study would fully survey all trees in a stand and then capture the corresponding harvester data set. This would allow a more complete understanding of what variation is attributable to the geospatial inaccuracy of the harvester versus the actual variation in the stand.

Chapter 5: Synthesis

Modern harvesters equipped with integrated technologies that automatically collect data, including information of time and space, through the integration of GNSS, have been extensively adopted in harvesting operations in fast growing forest plantations. The use of this technology in South America has mostly been restricted to operational reports, consequently, these readily collected information resources are underused, given the valuable opportunities for forest management analyses. As such, this thesis develops studies that prove we can take advantage of these technologies without any additional costs for collecting data, as we already have a data collection system included in the operations.

The quality of the harvester data is a vital factor; yet frequently, the reliability of the harvester measurements is questioned. However, it has clearly been demonstrated that proficient use of these machine measurement and control systems, with frequent calibrations and quality control activities, can ensure good quality data.

The harvester productivity study in Chapter 2, which integrated the information from stm and drf files, showed that this data is useful to assess machine productivity on an operational scale. The study can include many variables from the environment in digital format. For example, an advantage of the integration of GNSS is the ability to overlay the data capture by the harvester on topographic maps. This part of the study quantified the effect of DBH, species and operator. It found that shift and gentle slopes did not significantly affected the productivity of the wheeled harvester. The technology does have limitations however, as components of the harvesting cycle time cannot be isolated without direct observation. A limitation of this particular study's results is the use of a single machine to develop the productivity model. However, the goal is to prove the usefulness of the technology and thus new research could include more machines, different makes, different companies, and/or different regions of the country to create a more representative model. Further research should also apply this approach using other environmental variables such as terrain roughness; or to assess the effect of different conditions of the forest, e.g. compare sections of the forest affected by fire or wind throw with not affected areas.

From the study presented in Chapters 3 and 4, it was demonstrated that it is possible to map productivity from harvester data. It is important to understand the limitations of the accuracy of the tree location data. To better understand such limitations, a cell size analysis should be carried out for each area/stand as demonstrated in Chapter 3. This determines the cell size at which the coefficient of variation (CV) stabilizes for the productivity or stocking and mean tree volume. For the studied harvester data stands the cell size varied between 40 to 60 m. Forest stand yield maps can then be created, applying one of the models developed in Chapter 4. By using this approach, we can create productivity maps, which represent and quantify the variations at sub stand level better and more consistently than using inventory plots. However, there is still an uncertainty regarding the real effect of the inaccuracy of the records given by GNSS location (in the cabin of the machine) and the effect of forest coverage on GNSS records. An idealised future study would fully survey all trees in a stand and then capture the corresponding harvester data set. This would allow a more complete understanding of what variation is attributable to the geospatial inaccuracy of the harvester versus the actual variation in the stand.

This is the first published method to develop forest productivity maps from data automatically collected by harvesters. It creates a tool for studying productivity variations over short distances for large areas. This contributes to more efficient forest management, research, and the adoption of the concept of site-specific management on an operational scale in forest plantations in South America.

Further studies should create and overlay productivity maps with environmental information (soil maps, topographic maps) or stratify areas to run further studies (soil sampling for instance) so we can understand and manage the variables driving the differences in productivity.

Stem files (.stm) were the type of StanForD files found to be most useful and used for all studies in this thesis. We must take into consideration that stm files only record recovered volume and almost all data collected are commercial logs. Therefore, the mapped forest productivity refers only to commercial volume, not the total biomass volume of the stand.

From a broader perspective, the data recorded in StanForD files can be incorporated into many more studies. For example, the diameter sections measured at a 10 cm interval is comprehensive information useful for developing taper functions, as well as studying the variations in tree shape across areas. For example, it would be possible to compare edge trees with trees inside the stand. While other opportunities are presented throughout the thesis, future researchers and practitioners will be able to identify many additional opportunities for analyses and practical applications incorporating StanForD files, which will aid the industry to manage forest plantations more efficiently.

References

Acuna, M. A., & Kellogg, L. D. (2009). Evaluation of alternative cut-to-length harvesting technology for native forest thinning in Australia. *International Journal of Forest Engineering, 20*(2), 17-25. doi: 10.1080/14942119.2009.10702579

Adebayo, A. B., Han-Sup, H., & Johnson, L. (2007). Productivity and cost of cut-to-length and whole-tree harvesting in a mixed-conifer stand. *Forest Products Journal, 57*(6), 59-69.

Alam, M., Walsh, D., Strandgard, M., & Brown, M. (2014). A log-by-log productivity analysis of two Valmet 475EX harvesters. *International Journal of Forest Engineering, 25*(1), 14-22. doi: 10.1080/14942119.2014.891668

Andreoni, M. I., & Bussoni, A. (2014). Evaluación económica de dos programas de mejoramiento genético en Eucalyptus grandis. *Agrociencia Uruguay, 18*, 153-162.

Arlinger, J., Bergek, S., Hult, L., Larsson-Snygg, B., Morenius, B., & Sondell, J. (2011). Operational monitoring of forest machines under working condition: Definitions and implementations of time concepts and repair causes within the stanford framework - Version 3.0 (pp. 49). Sweden: Skogfork.

Arlinger, J., & Möller, J. (2007). *Information exchange with CTL machines, recent development of StanForD: A communication standard.* . Paper presented at the 3rd Forest Engineering Conference, Mont-Tremblant, Quebec, Canada. http://www.feric.ca/en/?OBJECTID=9D89028D-BC8C-A58C-9CFCBD334D266708

Arlinger, J., & Möller, J. J. (2014). *Time studies based on automatic data collection*. Paper presented at the 5th Forest Engineering Conference, Gerardmer - France.

Barbosa, C. E. M., Ferrari, S., Carvalho, M. d. P., Picoli, P. R. F., Cavallini, M. C., Benett, C. G. S., & Dos Santos, D. M. A. (2012). Inter-relação da produtividade de madeira do pinus com atributos físico-químicos de um latossolo do cerrado brasileiro. *Revista Árvore, 36*(1), 25-35.

Barth, A., & Holmgren, J. (2013). Stem taper estimates based on airborne laser scanning and cut-to-length harvester measurements for pre-harvest planning. *International Journal of Forest Engineering*, 1-9. doi: 10.1080/14942119.2013.858911

Biondi, F., Myers, D. E., & Avery, C. C. (1994). Geostatistically modeling stem size and increment in an old-growth forest. *Canadian Journal of Forest Research, 24*(7), 1354-1368. doi: 10.1139/x94-176

Bongiovanni, R., & Lowenberg-DeBoer, J. (2006). Adopcion de la agricultura de precision en el cono sur de America. In R. Bongiovanni, E. C. Mantovani, S. Best & Á. Roel (Eds.), *Agricultura de precisión:*

integrando conocimientos para una agricultura moderna y sustentable (pp. 203-218). Montevideo, Uruguay: Imprenta Mosca y CIA.

Bragachini, M., Méndez, A., Scaramuzza, F., & Proietti, F. (2006). Monitores de rendimiento y elaboracion de mapas. In R. Bongiovanni, E. C. Mantovani, S. Best & Á. Roel (Eds.), *Agricultura de precisión: integrando conocimientos para una agricultura moderna y sustentable* (pp. 43-54). Montevideo, Uruguay: Imprenta Mosca y CIA.

Bramucci, M., & Seixas, F. (2002). Quantification and determination of influency factors over harvesters productivity. *Scientia Forestalis, 62*, 62-74.

Brodbeck, C., Fulton, J., Shaw, J., McDonald, T., & Rodekohr, D. (2007). *Timber mapping for site-specific forest management*. Paper presented at the ASABE Annual International Meeting, Minneapolis, Minnesota, USA.

Burla, E. R. (2008). *Technical and economic evaluation of a "harvester" in eucalyptus timber cutting.* Magister Scientiae Dissertation, Universidade Federal de Viçosa, Viçosa Minas Merais – Brazil. Retrieved from http://www.ipef.br/servicos/teses/arquivos/burla,er.pdf (B961a)

Chen, Y., & Zhu, X. (2012). Site quality assessment of a Pinus radiata plantation in Victoria, Australia, using LiDAR technology. *Southern Forests: a Journal of Forest Science, 74*(4), 217-227. doi: http://dx.doi.org/10.2989/20702620.2012.741767

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing Environment, 37*, 35-46.

Cordero, R., Mardones, O., & Marticorena, M. (2006). *Evaluation of forestry machinery performance in harvesting operations using GPS technology.* Paper presented at the International Precision Forestry Symposium: Precision forestry in plantations, semi-natural and natural forests, Stellenbosch South Africa.

Crawley, M. J. (2013a). Mixed-effects models. In M. J. Crawley (Ed.), *The R Book* (Second ed., pp. 681-714). London, Uk: A John Wiley & Sons, Ltd.

Crawley, M. J. (Ed.). (2013b). *The R book* (Second ed.). London, Uk: A John Wiley & Sons, Ltd.

CRC for Forestry. (2010). *Enhancing forest machine efficiency: onboard computer selection and implementation guide*. Retrieved from http://www.crcforestry.com.au/publications/downloads/CRC-Onboard-Computers-WEBLINK-21_031.pdf

Cusano, N., Ettlin, G., & Ocaño, C. (2009). *Cosecha forestal mecanizada: Capacidad operacional y estudio economico de un sistema CTL (Mechanized forest harvesting: Operational capacity and economic study of a CTL system).* Agricultural Engineer Degree thesis, Universidad de la Republica, Montevideo, Uruguay. Retrieved from http://biblioteca.fagro.edu.uy/cgi-bin/wxis.exe/iah/ (T.3573)

Dell'Acqua, M. (2004). *Metodología e información utilizada para la elaboración de un modelo digital de terreno. Modelo Digital de Terreno.* Retrieved from http://www.prenader.gub.uy/coneat/doc/mdt.htm

du Toit, B., Smith, C. W., Little, K. M., Boreham, G., & Pallett, R. N. (2010). Intensive, site-specific silviculture: Manipulating resource availability at establishment for improved stand productivity. A review of South African research. *Forest Ecology and Management, 259*(9), 1836-1845. doi: http://dx.doi.org/10.1016/j.foreco.2009.07.015

Eriksson, M., & Lindroos, O. (2014). Productivity of harvesters and forwarders in CTL operations in northern Sweden based on large follow-up datasets. *International Journal of Forest Engineering*, 1-22. doi: 10.1080/14942119.2014.974309

Esri Inc. (2014a). ArcGIS 10.2.2 for Desktop (Version 10.2.2) [Geographical Information System]. United States of America: Esri.

Esri Inc. (2014b). *ArcGIS Help Library*

Fernandes, H. C., Burla, E. R., Leite, E. d. S., & Minette, L. J. (2013). Techinical and economic evaluation of a harvester under different terrain and forest productivity conditions. *Scientia Forestalis, 41*(97), 145-151.

Gerasimov, Y., Senkin, V., & Väätäinen, K. (2012). Productivity of single-grip harvesters in clear-cutting operations in the northern European part of Russia. *European Journal of Forest Research, 131*(3), 647-654. doi: 10.1007/s10342-011-0538-9

Gonçalves, J. L. d. M., Alvares, C. A., Gonçalves, T. D., Moreira, R. M. e., Mendez, J. C. T., & Gava, J. L. (2012). Soil and productivity mapping of Eucalyptus grandis plantations, using a geographic information system. *Scientia Forestalis, 40*(94), 187-201.

Gonçalves, J. L. d. M., Alvares, C. A., Higa, A. R., Silva, L. D., Alfenas, A. C., Stahl, J., Ferraz, S. F. d. B., Lima, W. d. P., Brancalion, P. H. S., Hubner, A., Bouillet, J.-P. D., Laclau, J.-P., Nouvellon, Y., & Epron, D. (2013). Integrating genetic and silvicultural strategies to minimize abiotic and biotic constraints in Brazilian eucalypt plantations. *Forest Ecology and Management, 301*, 6-27. doi: http://dx.doi.org/10.1016/j.foreco.2012.12.030

González Barrios, P., Pérez Bidegain, M., & Gutiérrez, L. (2015). Effects of tillage intensities on spatial soil variability and site-specific management in early growth of Eucalyptus grandis. *Forest Ecology and Management, 346*(0), 41-50. doi: http://dx.doi.org/10.1016/j.foreco.2015.02.031

Griffin, T. W. (2010). The spatial analysis of yiel data. In M. A. Oliver (Ed.), *Geostatiscal applications for precision agriculture* (pp. 27). United Kingdon: Springer.

Heinimann, H. R. (2001). *Productivity of a cut-to-length harvester family: An analysis based on operation data*. Paper presented at the Council on Forest Engineering (COFE) Conference “Appalachian

Hardwoods: Managing Change" Snowshoe - West Virginia - United States. http://web1.cnre.vt.edu/forestry/cofe/documents/2001/COFE_2001_Heinimann.pdf

Hiesl, P., & Benjamin, J. (2013). Applicability of international harvesting equipment productivity studies in Maine, USA: A literature review. *Forests, 4*(4), 898-921.

Holmgren, J., Barth, A., Larsson, H., & Olsson, H. (2012). Prediction of stem attributes by combining airborne laser scanning and measurements from harvesters. *Silva Fennica, 46*(2), 227-239. doi: 10.14214/sf.56

Holzleitner, F., Stampfer, K., & Visser, R. (2011). Utilization rates and cost factors in timber harvesting based on long-term machine data. *Croatian Journal of Forest Engineering, 32*(2), 501-508.

Instituto Uruguayo de Meteorología. (n.d.). *Estadísticas climatológicas.* Retrieved from http://www.meteorologia.com.uy/ServCli/caracteristicasClimaticas

Kaartinen, H., Hyyppä, J., Vastaranta, M., Kukko, A., Jaakkola, A., Yu, X., Pyörälä, J., Liang, X., Liu, J., Wang, Y., Kaijaluoto, R., Melkas, T., Holopainen, M., & Hyyppä, H. (2015). Accuracy of Kinematic Positioning Using Global Satellite Navigation Systems under Forest Canopies. *Forests, 6*(9), 3218-3236.

Köhl, M., Lasco, R., Cifuentes, M., Jonsson, Ö., Korhonen, K. T., Mundhenk, P., de Jesus Navar, J., & Stinson, G. (2015). Changes in forest production, biomass and carbon: Results from the 2015 UN FAO Global Forest Resource Assessment. *Forest Ecology and Management, 352*, 21-34. doi: 10.1016/j.foreco.2015.05.036

Leite, E. d. S., Fernandes, H. C., Minette, L. J., Leite, H. G., & Guedes, I. L. (2013). Technical and costs modeling of a harvester on cutting eucalyptus timber for the cut-to-length system. *Scientia Forestalis, 41*(98), 205-215.

Leite, E. d. S., Minette, L. J., Fernandes, H. C., Souza, A. P. d., Amaral, E. J. d., & Lacerda, E. d. G. (2014). Performance of the harvester on eucalyptus crops in different spacing and slopes. *Revista Árvore, 38*(1), 1-7.

Leonello, E. C., Gonçalves, S. P., & Fenner, P. T. (2012). Effect of time experience of harvester operators in operating yield. *Revista Árvore, 36*(6), 1129-1134.

Lindroos, O. (2010). Scrutinizing the theory of comparative time studies with operator as a block effect. *International Journal of Forest Engineering, 21*(1), 20-30. doi: 10.1080/14942119.2010.10702587

Lindroos, O., Ringdahl, O., Hera, P. L., Hohnloser, P., & Hellström, T. (2015). Estimating the position of the harvester head: A key step towards the precision forestry of the future? *Croatian Journal of Forest Engineering, 36*(2), 147-164.

Linhares, M., Sette Júnior, C. R., Campos, F., & Yamaji, F. M. (2012). Harvester and forwarder machines efficiency and operational performance in forest harvesting. *Pesquisa Agropecuária Tropical, 42*(2), 212-219.

Lyle, G., Bryan, B. A., & Ostendorf, B. (2014). Post-processing methods to eliminate erroneous grain yield measurements: Review and directions for future development. *Precision Agriculture, 15*(4), 377-402. doi: 10.1007/s11119-013-9336-3

Martins, R. J., Seixas, F., & Stape, J. L. (2009). Technical and economical evaluation of a harvester, working under different spacing and planting arrangement conditions in eucalypts plantations. *Scientia Forestalis, 37*(83), 253-263.

McDonald, T. P., Fulton, J., Darr, M., Taylor, S. E., Corley, F. W., & Brodbeck, C. (2006). *GPS-based documentation of manual silvicultural operations*. Paper presented at the International Precision Forestry Symposium : Precision forestry in plantations, semi-natural and natural forests, Stellenbosh, South Africa.

Mello, J. M. d. (2004). *Geoestatistica aplicada ao inventario florestal (Applied geostatistics to forest inventory).* Doctorate in Forest Resources, Sao Paulo University, Piracicaba, Sao Paulo, Brasil. (CDD 634.9285)

Mello, J. M. d., Batista, J. L. F., de Oliveira, M. S., & Ribeiro Jr, P. J. (2005). Spatial dependence sudy of *Eucalyptus grandis* dendrometric characteristics. *Cerne, 11*(2), 113-126.

Mello, J. M. d., Diniz, F. S., Oliveira, A. D. d., Mello, C. R. d., Scolforo, J. R. S., & Acerbi Junior, F. W. (2009). Continuidade espacial para características dendrométricas (numero de fustes e volume) em plantios de *Eucalyptus grandis*. *Revista Árvore, 33*(1), 185-194.

MGAP. (2008a). *Modelo Digital de Terreno.* Retrieved from http://www.cebra.com.uy/renare/mapa/modelo-digital-de-terreno/

MGAP, D. G. F. (2008b). *Compendio de Suelos del Uruguay (Compendium of Uruguayan soils)*. Retrieved from http://www.cebra.com.uy/renare/biblioteca-digital/

MGAP, D. G. F. (2014). *Extracion, produccion y consumo (Extraction, production and consumtion). Statistics and Market* Retrieved from http://www.mgap.gub.uy/portal/page.aspx?2,dgf,dgf-extraccion-produccion-consumo,O,es,0,

MGAP, D. G. F. (2015). Estadisticas forestales 2014 - Extraccion, produccion, consumo, mano de obra y comercio exterior *Estadisticas forestales* (July 2015 ed., pp. 52). Montevideo Uruguay: MGAP DGF.

Möller, J., Arlinger, J., Hannrup, B., Larsson, W., & Barth, A. (2011). *Harvester data as a base for management of forest operations and feedback to forest owners*. Paper presented at the 4th Forest Engineering Conference: Innovation in Forest Engineering – Adapting to Structural Change, White River, South Africa.

Murphy, G., Marshall, H., & Dick, A. (2014). Time of day impacts on machine productivity and value recovery in an off-forest central processing yard. *New Zealand Journal of Forestry Science, 44*(19), 1-9.

Murphy, G., Wilson, I., & Barr, B. (2006). Developing methods for pre-harvest inventories which use a harvester as the sampling tool. *Australian Forestry, 69*(1), 9-15. doi: 10.1080/00049158.2006.10674982

Nurminen, T., Korpunen, H., & Uusitalo, J. (2006). Time consumption analysis of the mechanized cut-to-length harvesting system. *Silva Fennica, 40*(2), 335-363.

Olivera, A., & Perdomo, N. (2011). *Evaluacion productiva de cosechadoras forestales en plantaciones de Eucalyputs ssp. en Uruguay (Productivity evaluation of forest harvesters in Eucalyptus ssp. plantations in Uruguay).* Uruguay.

Olivera, A., & Visser, R. (2014) Integration of Harvester Data and Geospatial Information. Harvesting technical note HTN07-03. Future Forest Research Ltd. Rotorua, New Zealand.

Olivera, A., Visser, R., Acuna, M., & Morgenroth, J. (2015). Automatic GNSS enabled harvester data collection as a tool to evaluate factors affecting harvester productivity in an *Eucalyptus* spp. harvesting operation in Uruguay. *International Journal of Forest Engineering*. doi: 10.1080/14942119.2015.1099775

Ortega, J. A., Foster, W., & Ortega, R. (2002). Definicion de sub-rodales para una silvicultura de precision: Una aplicacion del metodo fuzzy k-means. *Ciencia e Investigacion Agraria, 29*(1), 35-44.

Ortiz, J. L. (2003). *Emprego do geoprocessamento no estudo da relacao entre potencial produtivo de um povoamento de eucalipto e atributos do solo e relevo.* Master in Forest Resources, Sao Paulo University, Sao Paulo, Brasil. (CDD 634.9734)

Ortiz, J. L., Vettorazzi, C. A., Couto, H. T. Z. d., & Goncalves, J. L. d. M. (2006). Spatial relationship between productive potential of eucalypt and attributes of soil and relief. *Scientia Forestalis, 72*, 67-79.

Ovaskainen, H., Uusitalo, J., & Väätäinen, K. (2004). Characteristics and significance of a harvester operators' working technique in thinnings. *International Journal of Forest Engineering, 15*(2), 67-77. doi: 10.1080/14942119.2004.10702498

Palander, T., Nuutinen, Y., Kariniemi, A., & Vataainen, K. (2013). Automatic time study method for recording work phase times of timber harvesting. *Forest Science, 59*(4), 472-483. doi: 10.5849/forsci.12-009

Passicot, P., & Murphy, G. (2013). Effect of work schedule design on productivity of mechanised harvesting operations in Chile. *New Zealand Journal of Forestry Science, 43*(2), 1-10.

Payn, T., Carnus, J.-M., Freer-Smith, P., Kimberley, M., Kollert, W., Liu, S., Orazio, C., Rodriguez, L., Silva, L. N., & Wingfield, M. J. (2015). Changes in planted forests and future global implications. *Forest Ecology and Management, 352*, 57-67. doi: 10.1016/j.foreco.2015.06.021

Pereira, J. C., Mourão, D. A. C., Scalet, V., & Souza, C. A. M. d. (2011). Comparison between models of hypsometric relationship with and without spatial component for *Pinus sp.* at FLONA Ipanema - SP. *Scientia Forestalis, 39*(89), 43-52.

Pinheiro, J., Bates, D., Debroy, S., Sarkar, D., & R Core Team. (2014). Linear and nonlinear mixed effects models. Retrieved from http://CRAN.R-project.org/package=nlme

Ponsse Oyj. (2009). *Opti4G 4.700, Manual de instrucciones*

Ponsse Oyj. (nd.). Opti4G 4.715, Harvester software. Vieremä, Finland.

Purfürst, F. T. (2010). Learning curves of harvester operators. *Croatian Journal of Forest Engineering, 31*(2), 89-97.

Purfürst, F. T., & Erler, J. (2011a). The Human Influence on Productivity in Harvester Operations. *International Journal of Forest Engineering, 22*(2), 15-22. doi: 10.1080/14942119.2011.10702606

Purfürst, F. T., & Lindroos, O. (2011b). The correlation between long-term productivity and short-term performance ratings of harvester operators. *Croatian Journal of Forest Engineering, 32*(2), 509-519.

R Core Team. (2013). R: A language and environment for statistical computing. Viena, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/

Robert, R. C. G., Silva, F. A. P. C. e., Rocha, M. P. d., Amaral, E. J. d., & Guedes, l. L. (2013). Performance evaluation of a harvester 911.3 X3M operating on steep terrain. *Floresta e Ambiente, 20*(2), 183-190.

Robinson, T. P., & Metternicht, G. (2005). Comparing the performance of techniques to improve the quality of yield maps. *Agricultural Systems, 85*(1), 19-41. doi: http://dx.doi.org/10.1016/j.agsy.2004.07.010

Rombouts, J., Ferguson, I. S., & Leech, J. W. (2010). Campaign and site effects in LiDAR prediction models for site-quality assessment of radiata pine plantations in South Australia. *International Journal of Remote Sensing, 31*(5), 1155-1173. doi: 10.1080/01431160903380573

Silva, E. N. d. (2011). *Technical, economical and environmental evaluation of two forest harvesters* Doctor Scientiae, Federal University of Viçosa, Viçosa MG (T P324a 2011)

Silva, E. N. d., Machado, C. C., Minette, L. J., Souza, A. P. d., Fernandes, H. C., Silva, M. L. d., & Jacovine, L. A. (2010). Avaliação técnica e econômica do corte mecanizado de Pinus sp. com Harvester. *Revista Árvore, 34*(4), 745-753.

Simões, D., & Fenner, P. T. (2010). Influence of relief in productivity and costs of harvester. *Scientia Forestalis, 38*(85), 107-114.

Skogforsk. (2007). *Standard for Forest Data and communications* Retrieved from http://www.skogforsk.se/contentassets/b063db555a664ff8b515ce121f4a42d1/stanford_maindoc_070327.pdf

Skogforsk. (2015). *StanForD.* Retrieved from http://www.skogforsk.se/english/projects/stanford/

Spinelli, R., Hartsough, B. R., & Magagnotti, N. (2010). Productivity standards for harvesters and processors in Italy. *Forest Products Journal, 60*(3), 226-235.

Spinelli, R., Owende, P. M. O., & Ward, S. M. (2002). Productivity and cost of CTL harvesting of *Eucalyptus globulus* stands using excavator-based harvesters. *Forest Products Journal, 52*(1), 67-77.

Spinelli, R., & Visser, R. (2008). Analyzing and Estimating Delays in Harvester Operations. *International Journal of Forest Engineering, 19*(1), 36-41. doi: 10.1080/14942119.2008.10702558

Strandgard, M., Alam, M., & Mitchell, R. (2014). Impact of Slope on Productivity of a Self-levelling Processor. *Croatian Journal of Forest Engineering, 35*(2), 193-200.

Strandgard, M., Walsh, D., & Acuna, M. (2013). Estimating harvester productivity in Pinus radiata plantations using StanForD stem files. *Scandinavian Journal of Forest Research, 28*(1), 73-80. doi: 10.1080/02827581.2012.706633

Taylor, S. E., McDonald, T. P., Fulton, J. P., Shaw, J. N., Corley, F. W., & Brodbeck, C. J. (2006). *Precision forestry in the southeast U.S.* Paper presented at the International Precision Forestry Symposium - Precision Forestry in plantations, semi-natural and natural forests., Stellenbosch South Africa.

Taylor, S. E., Veal, M. W., Grift, T. E., McDonald, T. P., & Corley, F. W. (2002). *Precision Forestry: operational tactics for today and tomorrow*. Paper presented at the Council of Forest Engineering (COFE): A global perspective, Auburn - Alabama - United States. http://www.eng.auburn.edu/files/file169.pdf

Veal, M. W., Taylor, S. E., McDonald, T. P., McLemore, D. K., & Dunn, M. R. (2001). Accuracy of tracking forest machines with GPS. *Transactions of the ASAE, 44*(6), 1903-1911.

Vergara, J. T. (2004). Silvicultural options to increase the profit of plantation forest. *Bosque, 25*(2), 101-113.

Vieira, G. R., Garcia, C. W., & Zanardo, C. (2012). *Precision silviculture and performance monitoring in Brazilian Eucalyptus forest scenario*. Paper presented at the 45th International Symposium on Forestry Mecanization "Forest Engineerin: Concern, Knowledge and Accountability in Today's Environment", Dubrovink (Cavtat) - Croatia. http://www.formec2012.hr/

Visser, R., & Spinelli, R. (2012). Determining the shape of the productivity function for mechanized felling and felling-processing. *Journal of Forest Research, 17*(5), 397-402. doi: 10.1007/s10310-011-0313-2

Watt, M. S., Dash, J. P., Bhandari, S., & Watt, P. (2015). Comparing parametric and non-parametric methods of predicting Site Index for radiata pine using combinations of data derived from environmental surfaces, satellite imagery and airborne laser scanning. *Forest Ecology and Management, 357*, 1-9. doi: 10.1016/j.foreco.2015.08.001

Whelan, B., & Taylor, J. (2013). *Precision Agriculture for grain production systems*. Collingwood, VIC, Australia: CSIRO publishing.

Wing, M. G. (2008). Consumer-grade Global Positioning Systems (GPS) receiver performance. *Journal of Forestry, 106*(4), 185-190.

Wing, M. G., Eklund, A., & Kellogg, L. D. (2005). Consumer-grade Global Positioning System (GPS) accuracy and reliability. *Journal of Forestry, 103*(4), 169-173.

Yoshimura, T., & Hasegawa, H. (2003). Comparing the precision and accuracy of GPS positioning in forested areas. *Journal of Forest Research, 8*(3), 147-152. doi: 10.1007/s10310-002-0020-0

Zhang, N., Wang, M., & Wang, N. (2002). Precision agriculture—a worldwide overview. *Computers and Electronics in Agriculture, 36*, 113-132. doi: http://dx.doi.org/10.1016/S0168-1699(02)00096-0